University of Dundee

MASTER OF DENTAL SCIENCE

Testing the Use of Artificial Intelligence for Dental Age Estimation

Lygate, Anna

Award date:
2024

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Testing the Use of Artificial Intelligence for Dental Age Estimation

MDSc

2024

Anna Lygate

Supervisors: Dr Hemlata Pandey, Dr Scheila Mânica, Dr Ademir Franco, Dr Alex Gardner

Word count: 19,550 (excluding tables, headings and references)

Declaration

I, Anna Lygate, declare that I am the exclusive author of this project which is my own original work written in my own words, unless otherwise declared by references and external sources. This project conforms to the University of Dundee's policy on plagiarism and academic dishonesty and has not been previously submitted.

Acknowledgements

I would like to extend my thanks to the following people for helping me with my MDSc:

My project supervisors Dr Mânica, Dr Pandey and Dr Franco for their time, support, feedback and opportunities to develop my research and presentation skills throughout the project.

Dr Alex Gardner for his insight into programming for artificial intelligence.

Dr Andrew Mason for his guidance and advice at the initial stages of this project.

Artificial intelligence engineers Professor Andrew Abade and Mr Lucas Porto for their expertise in training and programming the DenseNet121 software.

Dr Gavin Revie for his advice on statistics and research design.

Lastly, my family and friends for their constant love and encouragement.

Abstract

Dental age estimation is a politically and ethically sensitive area of forensic odontology with great implications for individuals who are incorrectly classified: potential violation of a minor's rights, being denied access to appropriate services or adults in the system being treated as children such as in asylum seeker cases. The aims of this project are: To investigate the use of artificial intelligence (AI) on dental panoramic tomography radiographs to predict the age of an individual to be under or over 16; to evaluate how accurate AI is at correctly classifying images in the context of dental age estimation; to compare the performance of AI in estimating the dental of age males and females.

An observational analytics cross-sectional study was performed with a sample of 5040 radiographs of Brazilian subjects with 4200 used in training (n = 4200; 2100 males and 2100 females) between the age of 6 and 22.9 years, 16 years being in the middle of this range. The images were used to train and validate AI software (DenseNet121) to recognise patterns of the lower left mandibular third molar to classify the radiographs into two categories: over 16 or under 16 years old.

A stochastic optimisation algorithm (SGD) was used for optimisation during the training of the network. The images dataset was divided into 5 equal subsets, with four being used for training and the fifth to estimate the parameters and therefore compute the accuracy of the model. Results showed that DenseNet121 software could accurately estimate the age of both males (88% accuracy) and females (83% accuracy) by assigning them a binary result of either over 16 or under 16 years old. Confusion matrices and AUC graphs showed that classification by AI was more sensitive, specific and precise for males compared with females.

AI for age estimation using lower third molars was accurate with minimal difference between males and females, suggesting great potential of future development and use of AI in this field.

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List of acronyms

AI	Artificial Intelligence
ABFO	Americal Board of Forensic Odontology
ANN	Artificial neural networks
AUC	Area under the curve
CA	Chronological age
CBCT	Cone-beam computed tomography systems
CEJ	Cemento-enamel junction
CNN	Convolutional neural network

CT	Computed tomography
DA	Dental age
DAE	Dental age estimation
DMS	Dental maturity score
DPT	Dental panoramic tomography
FO	Forensic odontology (or odontologist)
FS	From scratch
GDP	General dental practitioner
GDPR	General Data Protection Regulation
GMAIU	Greater Manchester Immigration Aid Unit
ICE	Immigration and Custom Enforcement
M3	Third molar
MLP	Multi-layer perception
NIDJAM	National Inter-District Junior Athletics Meet
NSPCC	National Society for the Prevention of Cruelty to Children
PA	Periapical
PTVR	Pulp to toth volume ratio
ROC	Receiving operating characteristic
SGD	Stochastic optimisation algorithm
TL	Transfer learning

TPR	True positive rate
TW3	Tanner Whitehouse method
UK	United Kingdom
3D	Three-dimensional
2D	Two-dimensional

Introduction

Dental age estimation is a method performed by Forensic Odontologists that can be implemented in the living and deceased.[1] In the living, dental age estimation is often requested by legal authorities in cases that involve asylum seekers, child abuse and neglect, adoption and criminal imputability.[2]

In the deceased, it is performed for human identification where a biological profile of the victim(s) is built from evidence collected postmortem to estimate sex, age, stature and ancestry. The techniques available for dental age estimation can be invasive or non-invasive. Invasive techniques include the analysis of teeth *ex vivo*, and for this reason is only performed in skeletal remains or cadavers.[3] Non-invasive techniques may consist of direct visual inspection and radiographic analysis. Visual inspection can be limited because only the crowns are visible in the oral cavity however, radiographs enable an overview of both the crown and root development.

With developmental evidence, Forensic Odontologists can categorise teeth based on their formation stage.[4] Higher numbers of developing teeth give a higher accuracy of dental age estimation. This phenomenon occurs because the several teeth that develop simultaneously, especially in children, add age information to the statistical calculations used for an age estimate. In adolescents only third molars are developing, restricting the available dental age information.[5] This is the reason why recent studies test and validate the combination of developmental parameters (dental and skeletal) for better age estimation in practice.

The process of allocating developmental stages is subjective and depends on examiner's experience. To reduce the subjectivity, artificial intelligence by means of machine learning has emerged in recent years as an automated solution to overcome operator-dependent tasks in many areas of medicine and in forensic odontology.[6] However, training algorithms to recognize image patterns is challenging when it comes to the identification of teeth, especially during initial stages of the root development and the formation of the bifurcation, which can appear as a separate object from the crown.

An accurate age estimation has great legal importance and the use of artificial intelligence can reduce the examiner bias and the limitations of subjective dental stage allocation. Age estimations of 16 need to be accurate for the age of legal responsibility, age fraud in sports, becoming employed, joining the army, concerning the age of legal sexual consent, marriage and abortions.[7] Additionally, if a cadaver has been given an incorrect age estimation, this can lead to missing persons being excluded.[8] For these reasons, it is important that artificial intelligence is as accurate as possible, even when used to supplement manual methods rather than make decisions independently.

Chapter 1: Literature review

1) Dental development and age estimation

1.1 Dental development for age estimation

Tooth formation is a continuous process occurring throughout the whole developmental period of an individual.[9] Methods relying on tooth formation have been used extensively in forensic age estimation based on the qualitative and subjective assessments of tooth formation stages.

As age increases, the difference between between physiological and chronological age increases.[8] Therefore, dental age estimation techniques are highly reliable in children and less accurate in adults, where there is no conclusion over the most appropriate technique.[10]

Once dental and skeletal development is complete, age estimation may be based on skeletal and dental physiological regressive changes. However, regressive changes are altered by occupational, pathological and habitual factors.[8,11] Where there are missing teeth, other methods use skeletal information (pubic symphysis, ribs and osteon counts of bones) to estimate age but these are more influenced by environmental factors and ethnicity than dental methods.[8]

1.2 Dental age estimation in the living

For the living, age estimation can be used for judicial and civil problems concerning the age of children and young adults.[8] These include adoption, imputability, pornography, legal consent and child abuse or other similar matters where there are no identification documents. They are also requested for asylum seekers, sports players and juvenile offenders.[12]

Clinically, dental age estimation (DAE) and the analysis of dental development are required in oral medicine, paediatric dentistry and orthodontics, special care dentistry and dental radiology.[13] Treatment planning and the timing of development is important when using removable and fixed orthodontic appliances, particularly removable appliances to increase or decrease the rate of development of the maxilla and mandible in skeletal Class II and Class III cases.

1.3 Dental Age Estimation In The Deceased

For the deceased, DAE forms part of a biological profile to include or exclude individuals from an antemortem established age-based list to limit the search of the missing persons list.[14] The biological profile of an individual will also include the sex, stature and ancestry estimate with the aim of reaching a positive identification. This is done through a physical examination and assessing skeletal and dental development.

DAE is one of the most simple and reliable biological methods to estimate the age of skeletal remains.[15] For remains in poor condition, dental tissues are more resistant to thermal, chemical and mechanical factors and are less affected by endocrine diseases and nutritional variations than other tissues.[16]

A comparative analysis is completed using antemortem data (provided by the clinical dentist) and postmortem data (from the Forensic Odontologist in the mortuary).[17]

The error range of the method used is crucial because if the age of the individual lies outside this range, the target individual may be excluded.[8] For example, if a method gives an age range of 30-45 but the missing person is 47 years old, this excludes the missing person. Therefore, forensic reports frequently have age estimations within a large age range in adults.

2) Assessing dental development using radiographs

Radiographic methods of DAE are commonly used due to the availability of antemortem and postmortem records and due to the ease of the availability of retrieving radiographs.[18] In modern Dentistry, radiographs are extensively used for diagnosis and clinical practice and can be used to obtain continuous data, particularly in orthodontic patients who have thorough documentation, including photographs from dental records that can be used for DAE.[19]

2.1 Dental Panoramic Tomographs

Dental panoramic tomographs (DPTs) are commonly used to view the full upper and lower jaws and have the advantage of being easier to take in young or nervous children and give less radiation than several PA's to view the entire dentition.[20] Despite this, a practical drawback of using DPTs is that superposition can impede anatomical features of interest, preventing the correct developmental status which result in observer errors.[21]

Distortion will cause the image will also have a 3-10% enlargement of the mandible but for research and DAE methods, this can be overcome where shape criteria and relative values are used for comparison rather than absolute lengths.[4]

2.2 Dental periapical radiographs

Measurement of tooth proportions (pulp tooth volume ratio or PTVR) radiographically is a non-invasive method of age estimation.[22] Age correlates with a reduction in volume of the pulp chamber due to secondary dentine deposition over time which can be seen using several radiographic views: DPT, periapical (PA) and maxillary occlusal.[23]

Kvaal's method is used for the developed dentition in adults and uses individual tooth measurements from a DPT at several landmarks along the long axis of teeth.[22] This can be done using two-dimensional or three-dimensional images.[24] Vertical measurements are: tooth length (T), pulp length (P), root length (R). Horizontal measurements are: pulp width at ECJ (A), pulp width midway between apex and CEJ (B) and pulp width midway between A and C shown in figure 1.

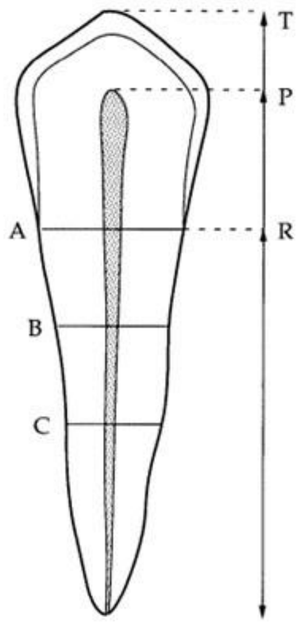

Figure 1: Example vertical landmarks for PTVR methods.[22]

The vertical and horizontal measurements are used in a linear regression equation for age estimation. Several studies have shown higher correlation of root width ratios with age than length ratios[25,26] and point B shows the highest correlation with age.[25]

However, measurements could not be made on teeth which were impacted, had tooth-associated radiopacities, restorations, crowns, apical pathological processes, had been root-filled, or which had a mesiodistal plane which was not parallel to the film.

Although Kvaal's method was developed using DPTs, this method can also be done using dental intraoral periapical radiographs as seen in a study by Rajpal et al. (2016).[27] Individuals in Rajpal's study were aged between 15-57 years and the teeth most useful for determining age were the maxillary and mandibular central and lateral incisors and mandibular second premolars. Multirooted teeth and canines are not as useful for applying age estimation methods.[22] Rajan agreed that width ratios are more correlated with age than length ratios despite differences in the location of dentine formation.

A more recent study from Akhlaghi et al. (2020) estimated chronological age using dental periapical radiographs with Kvaal's method using Scanora software to measure the distance between landmarks and found point B and C (fig 2) could be used for age estimation in an Iranian adult population.[28]

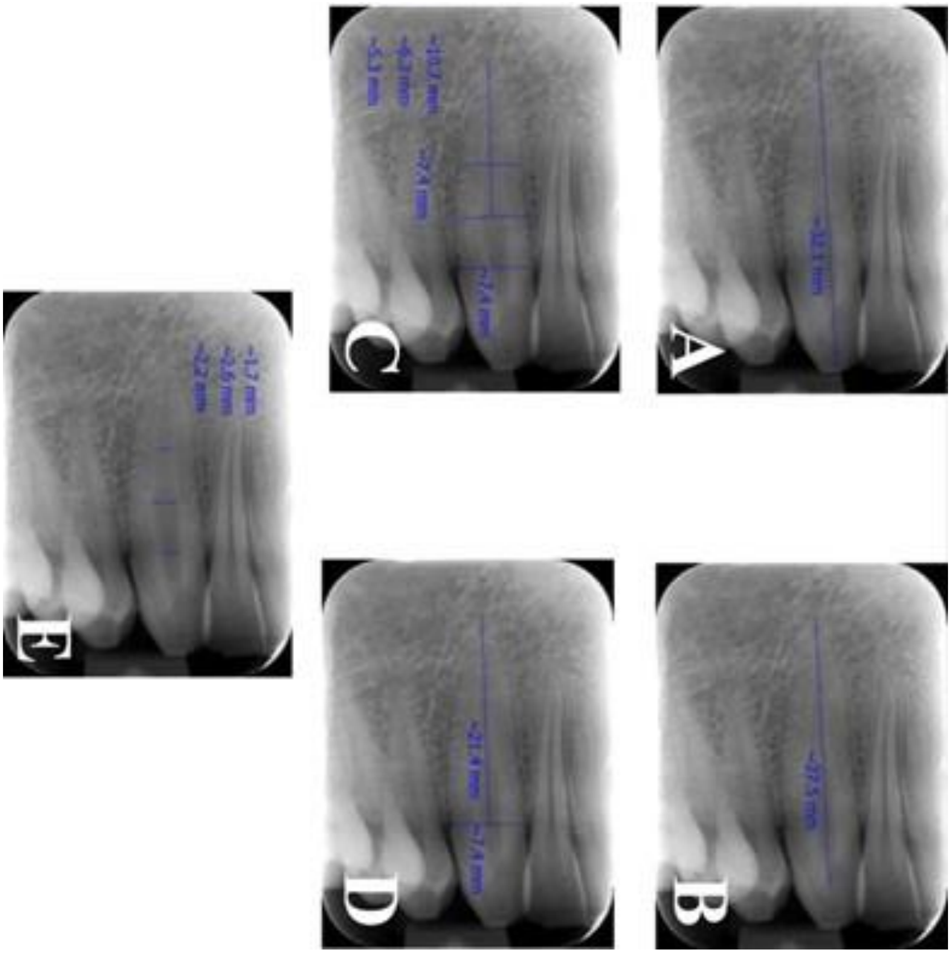

Figure 2: A. Tooth length; B. Pulp length; C. Root length; D. Root width at points A, B, and C; E. Pulp width at points A, B, and C.[28]

For PTVR methods, 3D imaging from CBCT scans can overcome the challenges of using 2D imaging.[29] However, the fact still remains that the relationship between pulp volume and age is not always linear[30] as shown in some studies with larger sample sizes where the reduction of pulp volume is inconsistent at different ages, producing a sigmoid curve.[30, 31] This means that there are challenges with the application of PTVR in age estimation cases.[30]

2.3 Artificial intelligence using periapical radiographs

Radiological methods are relatively straightforward, reproducible, non-invasive, and can be performed on the living and the dead. Skilled and experienced observers would normally carry these out precisely and reproducibly as there is a detailed process required but recent advances in research and technology are using AI to perform these tasks. For example, Zaborowicz et al. (2022) proposed the use of deep neural network models to provide age estimation of children and adolescents from dental images.[32] The proposed study aimed to construct a more accurate model than those previously produced.

AI has been used on periapical radiographs to detect periodontitis[33,34] and for automatic detection and numbering of teeth[35] but there are no known studies investigating using AI on periapical views for DAE.

2.4 Ethical issues of radiographic methods

Using radiographs is a controversial method for DAE because it requires exposure to ionising radiation which comes with associated risks.[36] According to the Oxford University Hospitals NHS Foundation Trust Referral Criteria and Exposure Protocols Guidelines, any referral for radiographs should have justified exposure and the radiographer needs to be satisfied with the information provided by the referrer.[37]

Kapadia et al. (2020)[38] looked at the methodological, ethical and health issues associated with using dental radiographs to visualise the third molar for DAE in migrant children seeking asylum status in the United States:

> “The application of third molar dental radiographs is methodologically flawed and should not be employed as a determinant of chronological age. Furthermore, the use of such tests

> without obtaining informed consent from either the youth or an objective advocate is unethical…Finally, the legal and health consequences of these inappropriately applied tests are severe and jeopardise the safety and security of these vulnerable minors."

Additionally, the British Dental Association states that using dental radiographs to confirm the age of those seeking asylum in the UK is "inaccurate, inappropriate and unethical."[39] Several countries prohibit the use of ionising radiation for asylum and civil procedures[40] and the reliable method of age estimation through hand-wrist radiographs now has limited clinical application due to the dose of ionising radiation to children.[41]

3) Features of the dentition for age estimation

3.1 Tooth eruption

There are two approaches for DAE in children: clinically assessing tooth eruption intra-orally or to radiographically assess tooth mineralisation and development.

Although tooth eruption has been used to estimate the age of death of skeletal remains, eruption occurs over a short period of time and only represents the stage in the process where the tooth reaches the occlusal plane. Eruption can be affected by local factors (ankylosis, infection, crowding of permanent teeth, early or delayed extraction of the deciduous tooth) and systemic factors (nutritional status).[42, 43] Its accuracy is also compromised by periods where no tooth eruption occurs or where several teeth erupt simultaneously[44] and the rate of formation of permanent teeth is affected by premature loss of the deciduous teeth.[45] Therefore, tooth formation and calcification is a more reliable indicator of dental age than eruption.

Calcification during early tooth formation is visible radiographically. Barka et al. (2013)[46] studied third molar development in Greek orthodontic patients where early signs of tooth formation were seen by the presence of uncalcified crypt or by the mineralisation of cusp tips.

Dissected material of cadavers will show a younger age compared with radiographs because the dental tissue needs a greater degree of calcification before being visible radiographically.[47] For example, the first permanent molar is not visible radiographically until 6 months of age despite being calcified prenatally.

3.2 The use of atlases in dental age estimation

Whilst the presence and study of tooth and root formation can indicate age, a more accurate method for DAE of the developing dentition is based upon the sequence of eruption and the degree of calcification to provide an index.[19] Teeth develop in a predictable sequence from before birth until early adulthood[48] and where there are several developing teeth, there is more information for an accurate age estimation.[44]

There are several atlases used for DAE: Schour and Massler Atlas,[49] Uberlaker Atlas and the London atlas.[50] The first, and the most well-known, atlas is the Schour and Massler Atlas developed in 1941. This includes a series of drawings showing the development at 21 stages from in-utero to young adulthood. However, the time between development stages is not consistent (consecutive up to age 12 where the next stage is 15 years old) and few details of the sample are known such as the material or method of analysis. Later revisions in 1944 have been made to this atlas using radiographs.

Secondly, the Uberlaker Atlas was developed in 1978 and was based on the Schour and Massler Atlas. It uses a number of published sources and notes a range of variation present at each stage of development, along with a line indicating the level of gingival emergence. Modifications have been made to Uberlaker's charts by adjusting the age allocated to each drawing based on sex.[51]

Most recently, the London atlas of tooth development and eruption looks at the development of the entire dentition from mineralisation and eruption to full root completion. This tooth-specific atlas is often used clinically to assess dental development of children. Unlike the Schour and Massler atlas, this is an evidence-based atlas that attempts to overcome the challenges of previous atlases by having all age categories illustrated and shows the enamel, dentine and pulp.[51]

3.3 Factors affecting development

The literature has shown that the methods of DAE based on the mineralisation and growth stage of the teeth depends on the genetics of the populations (due to ethnic variability)[8] more than local and systemic factors.[52]

Other factors affecting dental age outcome include:[53]

1) Method errors
2) Methodological over and underestimations of age
3) Sex of an individual
4) Age of individuals

The experience and knowledge of the forensic odontologist is essential as the process of estimating the stage of tooth development of young adults is highly complex.[54] This is where accurate automated methods using AI have the potential to overcome manual errors.

4) Staging methods

4.1 Ordinal staging

Ordinal staging of the crown and root formation is one of the most frequently used techniques for establishing the tooth developmental status in forensic odontology.[12] Each method varies in the number of teeth used as this is specific to the parameters set out by the authors of the method.

4.2 Demirjian 1973

Demirjian's method of age estimation is one of the most widely applied methods of DAE which looks at the stages of tooth development, and lettering them from A to H (fig 3).[4] DPTs of 1446 French Canadian boys and 1482 girls aged 2-20 years were analysed and the teeth categorised into stages A-H. Each tooth is allocated a stage, and the sum of the scores gives an evaluation of the subject's dental maturity. The dental maturity score (DMS) can be converted into the dental age (DA) using available tables.

Then, the percentile curves are allocated, and the sum of the scores provides the subject's dental maturity. Differences between the dental age (DA) and chronological age (CA) of a subject may indicate an advanced or delayed dental maturity.[52] This method can be used for children aged 3-17 years.

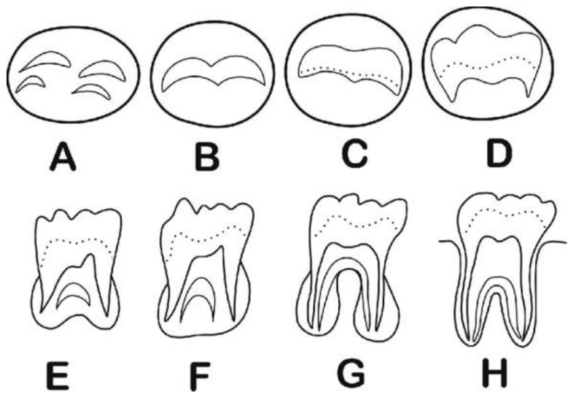

Figure 3: Stages in Demirjian's method.[4]

French Canadian children are more dentally advanced than others so Demirjian's method has commonly been reported to overestimate age by over 6 months.[55]

4.2.1 Studies investigating Demirjian

Jayaraman et al. (2013) investigated the applicability of Demirjian's method to different geographical groups by using the method on 19,599 subjects aged between 2 and 21 years belonging to different global population groups.[53] The Demirjian method overestimated the age of females by 0.65 years (-0.10 years to +2.28 years) and males by 0.60 years (-0.23 years to +3.04 years).

Overestimation was most reported in most populations. However, in Jayaraman's study, maximum variation was found in Indian subjects and an underestimation of age was present in Venezuelan and Western Chinese males and Venezuelan females. The overestimation of age is supported by other studies which found an overestimated age in Polish[56] and Hungarian[57] populations using Demirjian's method. However, literature supports using Demirjian's method in North-eastern Turkish children, Malay population, Western Chinese children, Belgaum population and Lucknow children.[58]

4.3 Haavikko (1974)

Haavikko et al. (1974) developed a model based on 12 radiographic stages of each developing permanent tooth to create a simple and reliable age estimation method that could be used for individuals with hypodontia.[59] This method included radiographs where individuals with considerable developmental delay were included in the full analyses.[60] Haavikko designed this method to be used in forensic scenarios and for clinical purposes.

Importantly, Haavikko concluded that no age estimation can accurately determine the exact age for every individual due to development variability between individuals. Furthermore, the most important aspect of DAE is to apply several techniques with reproducible calculations and measurements rather than being restricted to only one technique.

4.4 Cameriere method (2008)

Cameriere at al. (2008) developed a new radiographic method for assessing the age of adults using the ratio of age and the measurement of the open apices and height of the third molar of Italian individuals. The method identifies a threshold used to differentiate between individuals who were above or below 18 years of age,[61] the age of legal majority in many countries.

Recently, machine learning of the Cameriere formula has been shown to produce an age estimation more accurately and efficiently than the traditional formula.[62]

4.5 Willems (2014)

The later developed Willems method[63] is a modified Demirjian method which is more accurate and aims to overcome the overestimation of age. Willems found that adaptations to the method for specific populations can improve the accuracy of age estimation.

However, even Willems method has limitations as it requires all mandibular teeth to be present (apart from the third molar) but the second mandibular premolar is one of the most frequently missing teeth.[64, 65] This highlights the importance of being able to use all landmarks on a DPT and methods which are not limited to the development of specific teeth for an accurate age estimation.

5) Age estimation from specific teeth

5.1 Important teeth for dental age estimation

Haavikko et al. (1974) also investigated which teeth had the least variation to determine whether estimates of a tooth formation age could be done using only a few selected teeth, and which teeth would give the most reliable developmental stages.[66]

They concluded that the teeth most reliable for use in age estimation were different depending on the age of an individual: tooth 46, 44, 41 from ages 0-9 years and tooth 47, 44, 43 from age 10-13 years. Most teeth were fully formed at 9-10 years, with the exceptions of teeth 47 and 44. On the other hand, the second premolar and upper lateral incisors were the most variable teeth.

The development of teeth on the mandible were easier to visualise and assess than the maxilla on DPTs so the formation stage was more accurate. Teeth that were rotated, misplaced and crowded were harder to accurately analyse.

5.2 Mandibular third molars and adults

Mandibular third molars are important teeth (despite their variability in development, eruption anatomy, size, contour and anatomical orientation) as radiographically, they have minimal distortion and superimposition of hard tissue, soft tissue and bone in comparison to maxillary third molars.[67] Distortion and superimposition can further be minimised with downward positioning of the chin during exposure.[68]

What is arguably more important is that there are very few alternative teeth to use for adolescents and young adults, since all other teeth have erupted and completed their development by this age.[69]

5.3 Dental age estimation for age 18

The reliability of correctly identifying a subject as being over or under 18 was done by Lucas et al. (2016) using the 'gold standard' which is Demirjian's method due to its high level of reproducibility and robust results.[70] Subjects were aged 16-26 years and the results showed no statistical difference between males and females using Demirjian's method.

Lucas found that the threshold of being above or below 18 in the age range of 17-19 years could be incorrect on up to 50% of occasions. The probability assessment was not sensitive to subjects with a chronological age close to 18 years, giving a judicially undesirable result of subjects over 18 years being assessed as under 18 years, an outcome which is unacceptable and ethically unacceptable.

5.3.1 Drawbacks of relying on third molars

There are several practical problems with relying on third molar development. Firstly, on a DPT there is often poor visualization of the maxillary third molar (from superimposition and distortion around the maxillary tuberosity) until cusps are calcified which makes it difficult to identify in the earlier stages of development.[71]

Secondly, high levels of agenesis in a population prevents means there may be no remaining developing teeth. Mandibular third molars are frequently congenitally missing in 17.6% of cases but this may be higher or lower depending on the population.[72,73]

Thirdly, third molar extractions may be performed for prophylactic reasons[74] between the ages of 20 and 39 years old however, third molars are in their final stages of root formation at this age.[75]

6) Role of CBCT in age estimation

6.1 Combining CBCT and DPTs for DAE

Despite DPTs being the gold standard for staging development, there is the possibility of using CBCT scans to visualise developing teeth and classify them into stages. A study by Franco et al. (2020) compared the developmental staging of DPTs and CBCTs and extracted (fig 4) third molars which had complete completely developed crowns, were not restored and had no decay.[12]

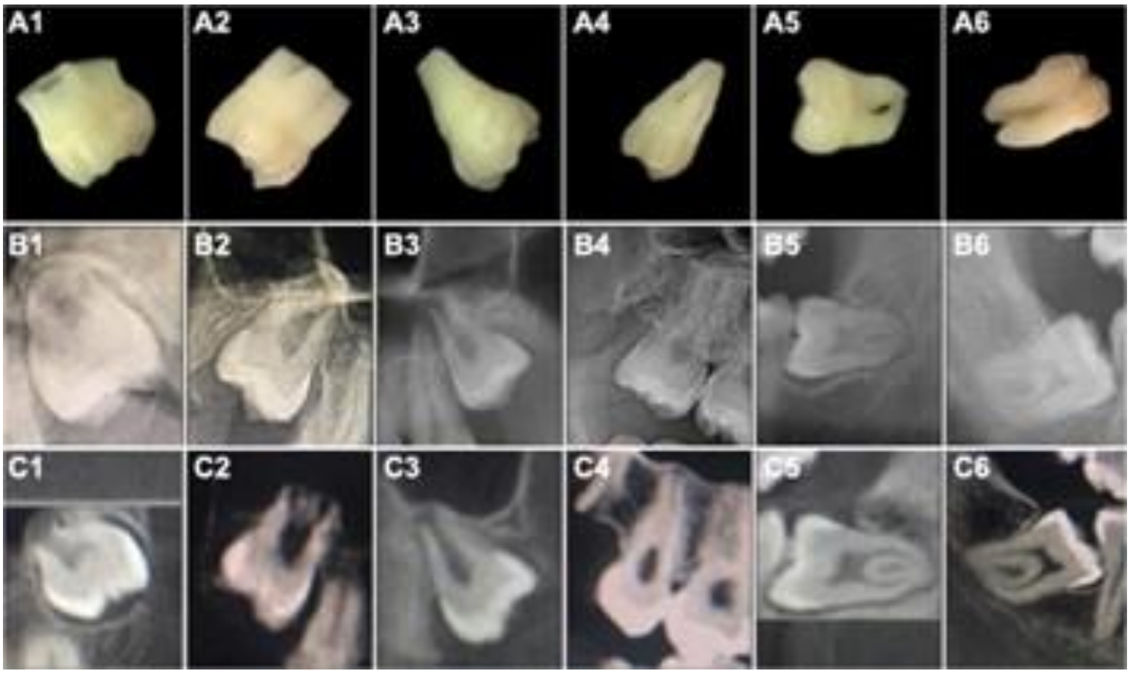

Figure 4: Comparison of an magnetic resonance image scan, dental panoramic tomograph and extracted teeth.[12]

Two examiners staged the teeth using the Kohler et al. (1994) modified Gleiser technique[76] which classifies development using the crown, root and apex development of third molars. This is a particularly useful method for late development of molars to determine if an individual is an adult or minor.

The paper suggested that the 3D visualisation could overcome the limitations of a 2D radiograph, however, extracted teeth and DPTs are more similar than CBCT and DPT images. Results showed that there were minor discrepancies in stage allocation between DPTs and CBCTs, with DPTs being the gold standard for age estimation. In situations where there is no imaging equipment, extracted teeth may be useful.

6.2 Multifactorial age estimation

Most other studies looking at 3D imaging use a combination of anatomical sites such as teeth, clavicles, hand and wrist development to give a multifactorial age estimation which can be used to extend the age range from 18 to 25 years old.[77] A later study by Tobel et al. (2020) used MRI imaging for age estimation in living children by looking at MRI scans of subjects up to 30 years old.[78] Anatomical sites used were the skull, teeth, chest, hip, upper limb and lower limb. They found using a multifactorial age estimation method was more accurate than a single anatomical site, with the apical closure of teeth being an important feature.

6.3 MRI scans for dental development

Štern et al. (2017)[77] studied MRI scans for age estimation using only tooth development rather than a multifactorial approach. Their paper focused on the lack of standardised methods and intra- and inter-observer bias in analysing and staging images and concluded that caution should be taken classifying an individual as an adult or minor as this requires a high level of sensitivity.

7) Examiner bias of age estimation and AI

7.1 Observer variation compared to AI

Evaluation of radiographs or any medical images for forensic age estimation is performed by expert human observers such as forensic anthropologists, radiologists or forensic odontologists who are experienced in analysing the developmental status of anatomical structures shown in medical images. The experience, training and exposure of these experts is important however, recent developments in AI allow it to recognise patterns and use decision-making processes to give accuracy similar to humans.

For example, De Tobel et al. (2020) studied the use of AI in staging radiographic third molar development and compared this with two human observers allocating the same stages.[78] Results of the AI model were equivalent to trained human observers. Although only 51% of the stages were correctly allocated by the software, misclassified stages were in the neighbouring categories.

Misclassified stages by human observers were mostly due to an intermediate stage of development or using an unclear radiograph[79] so, in instances where the two observers disagreed on the stage, a third observer would act as a referee to come to a conclusion. Other issues noted in this study were that relying on one tooth, particularly the third molar, is problematic as agenesis and impaction were common as shown in figure 5.

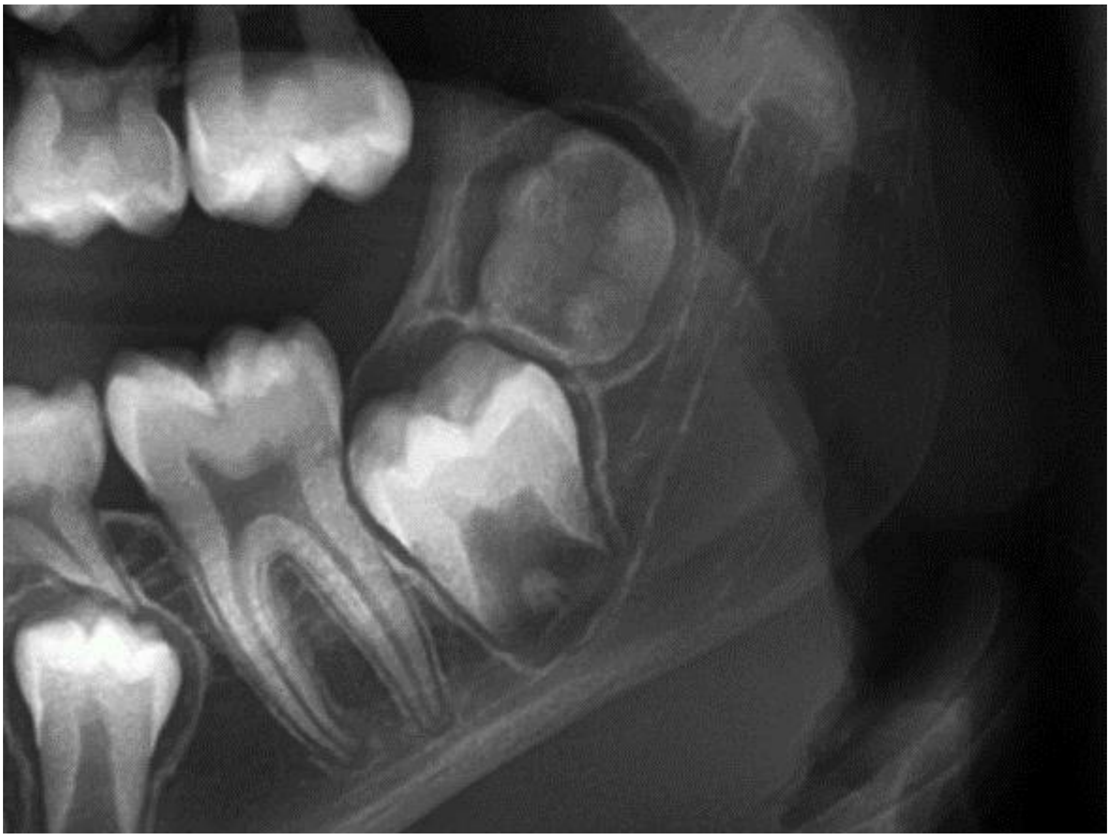

Figure 5: Rotated lower third molar.[78]

Importantly, Tobel's paper noted that the observer-induced variability could also be applied to an AI system through training because errors during the annotation of the training data will then be replicated by the neural network.

7.2 Training and examiner bias

Pillai et al. (2021) conducted a study to determine the inter-observer agreement in radiographic interpretation using Demirjian's method on mandibular second and third molars.[80] Some 123 DPTs of individuals aged 5-22 years were evaluated and staged by four observers with different levels of experience in age estimation: one experienced forensic odontologist, two recently qualified dentists with postgraduate training in forensic odontology and a general dental practitioner (GDP) with no training in dental age estimation. The radiographs were randomly selected and information on the age and sex of the patients was hidden.

The observers then individually assigned each radiograph a developmental stage based on the Demirjian and Chailet's 10 stage chart with the forensic odontologist's scores used as a reference for comparison. The DPTs were then re-evaluated at a later date.

It was found that there was a significant agreement for both the second and third molars by the observers for both the initial and re-evaluation grades. The percentage agreement with the forensic odontologist was least for the GDP who had no prior training (theoretical or practical) in the radiographic dental age estimation method. Training in applying the classification system by the experienced forensic odontologist improved the results and gave greater agreeability between observers, with a smaller range of stages for each DPT.

Pillai's study found that the **"**third molars exhibit marked differences in terms of formation, eruption morphology, and agenesis compared to the second molar. That could be attributed to the significant difference in scoring and a lesser agreement by all the observers in this study." They concluded that adequate training in radiographic interpretation and the use of reference digital radiographs with the ability to change the contrast and magnify the image minimised errors.

Training for dental age estimation gives time and experience for calibration and, from a legal perspective, age estimation methods need to be accurate and reproducible with minimal interobserver variability regardless of their experience. Using AI to perform these tasks may eliminate the bias between humans by using efficient automated methods.

8) Artificial Intelligence in FO

8.1 Artificial Neural Networks

Artificial intelligence in the medical field can automatically diagnose radiographic images via a process known as deep-learning. Since 2017, the accuracy of AI has already surpassed human accuracy.[81] Additionally, the techniques require less time than manual human evaluation and the repetitive tasks will not cause fatigue as is the case for humans.[82] For example, estimating an individual's chronological age using the Demirjian-Chaillet method can take a human observer on average 10 minutes.[83]

Artificial Neural Networks (ANN) simply identifies and interprets unknown patterns by machine learning to diagnose and make predictions through training using large volumes of input data.[84] ANNs have processing elements (or neurons) which are units which can be adjusted through a process of training, learning and generalisation.[85] The behaviour of an ANN is determined by the organisation of the neurons and the weights of the connections between them. The value of the weights is learned through an algorithm which finds the optimal configuration of the weights for the desired outcome.

Deep-learning has shown excellent performance in image classification, segmentation and detection. Therefore, using ANN models can accelerate the process of classifying radiographs because the mathematical formula implemented by the algorithm automatically allocates the data into categories and classes. However, understanding the decision-making process of a deep neural network is complicated and difficult to understand as it is based on mathematical models.

8.2 Sex determination using artificial intelligence

AI is not limited to categorisation of data for age estimation purposes only. Fidva et al. (2018)[86] used the canines to determine sex using AI. For this study, 100 measurements of the diameter of mesiodistal, buccolingual, and diagonal upper and lower canine jaw models (50 male and 50 female) were uploaded to a computer program which had algorithms to recognise patterns in the images. This acted as the training for the computer program. Once the pattern was obtained and classification model applied, the determination of sex was performed. The accuracy rate of sex determination was 84% using a multi-layer perception (MLP) method.

8.3 AI in age estimation using dental panoramic tomographs

ANNs have been researched in FO for the purposes of DAE for identification using developmental milestones seen in teeth and anatomical landmarks on radiographs. The AI focuses on different areas of the image depending on the age. In 2020, Vila-Blanco et al. (2020) studied the use of ANNs to estimate age in 1752 DPTs which were split into 'perfect' and 'imperfect' categories. Unlike many other studies, the 'imperfect' radiographs were included (images showing orthodontic appliances, prostheses, implants, restorations, jewellery, hypodontia, retained roots and distorted or blurred areas).[87]

The network's behaviour was analysed and the areas of learned features were shown on the output image as a heatmap. Then the estimated chronological age was estimated and compared to the opinions of clinical dental experts. Figure 6 shows a heat map, with the 'hotspot' areas highlighting where more attention was paid to the AI. Different age groups had different areas which were most important for giving the desired output of chronological age.

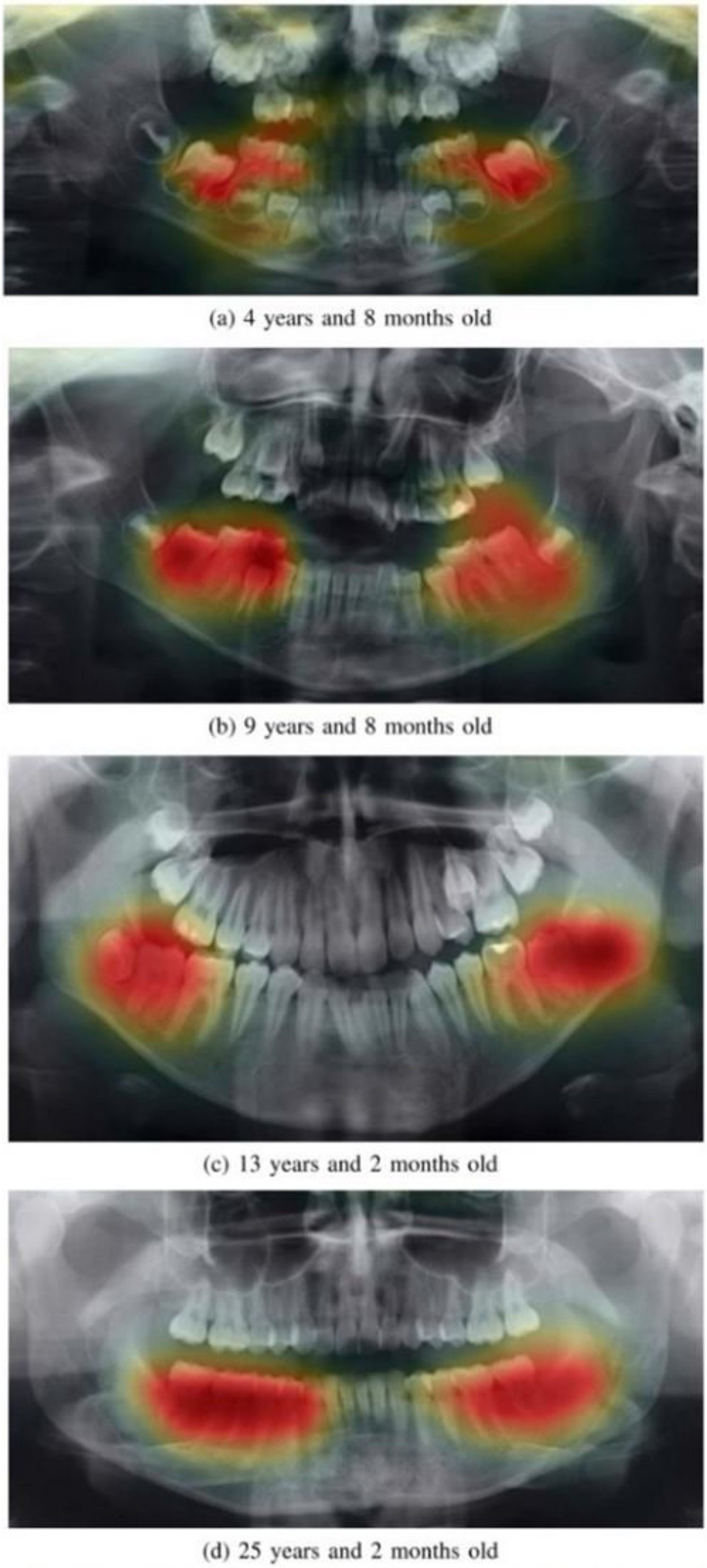

Figure 6: Heat map showing areas paid attention to by the network at age 4, 9, 13 and 25 years.[87]

The results showed that the model trained with only subjects under 15 years was more accurate for estimating a child's age compared to using a sample with the full age range. The accuracy of the network worsened when older individuals, over 25, were included because the permanent teeth were completely formed so had less developmental anatomical variation. Therefore, models can be adapted to be more accurate with target ages and populations.

This study concluded that using AI and deep learning has the potential to make improvements in time and subjectivity of age estimation, especially in children and adolescents with developing dentitions.

Back et al. (2019) used convolutional neural networks (CNNs) on DPTs for age estimation.[88] This study recognised that current scoring-based methods for age estimation require expensive training and have poor inter-rater variability and additionally, using staging methods such as Demirjian's method is time-consuming and subjective based on the observers. Therefore, using AI to estimate age may overcome these challenges.[89]

A set of 2400 DPTs were used after the software was trained to predict true chronological age, however, the mean absolute error for the validation set was almost two years which was considered unacceptable for use in legal purposes. Saliency maps were generated for different age ranges to construct 50 maps of random images. The saliency maps showed the most informative regions were around the molars which was the predicted result. As seen below (fig 7), the model used the maxillary sinus as a marker for younger age ranges and the nasal septum for older age ranges.

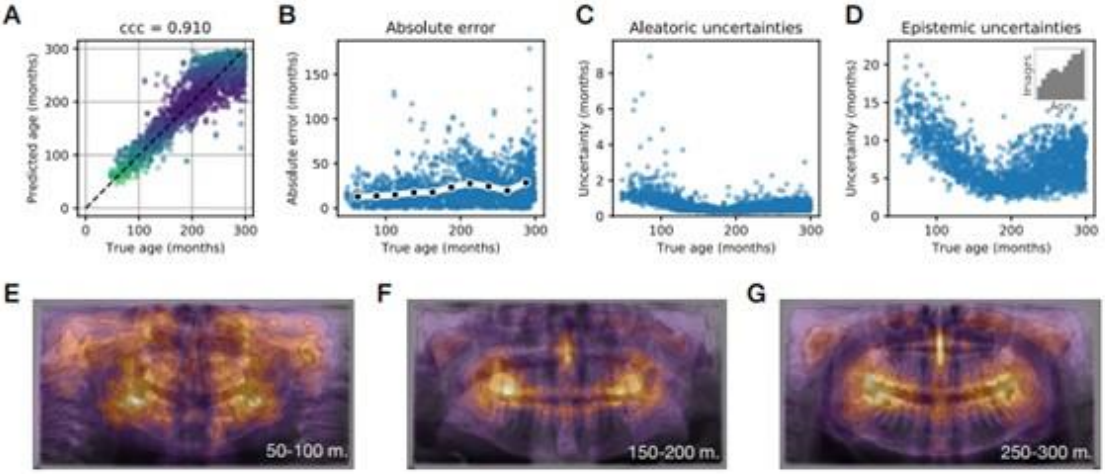

Figure 7: Results showing the correlation between true and predicted age and saliency maps for different age groups.[88]

The results of this study showed there is more uncertainty for sub-adult age estimation as there are fewer biological markers of dental development. However, the patterns in the saliency maps may reveal new potential markers for age estimation from DPTs which may not be obvious to a human observer and is not limited to manual staging methods of teeth for age estimation of sub-adults.

Back's system shows a quantitative estimation of prediction uncertainty and explanatory saliency map which are important in indicating the accuracy of age estimation, especially around a majority age classification which is important in a legal context.

8.4 AI for MRI age estimation

Štern et al. (2019) used a similar deep learning system for multifactorial age estimation using MRI data from third molars, clavicles and hand bones to extend the maximum age range from 0-19 years to 0-25 years. Some 322 subjects between 13 and 25 years were used to train the AI which analysed the images and fused age-relevant information to give a multifactorial age estimation.[90]

Third molars were found to be influential on age estimation between the age of 17 and 22 years, however, these were commonly missing. For estimating age 16 to 19 years, the highest estimation accuracy used both the third molar and clavicle development combined. Additionally, the advantage of using MRI data reduced observer variability and avoided using ionising radiation.

8.5 Artificial Intelligence for sex estimation

Patil et al. (2020) used ANNs for sex determination using mandibular parameters in a comparative retrospective study from 2020.[91] The process of sex determination is automated with minimal errors and proves a promising advancement in AI for FO. The technology is based on a mathematical model to mimic human brains and can identify patterns and classify DPTs into male and female. To assess the reliability of this method, the results were compared to measurements made by two radiologists.

Some 509 radiographs were analysed and the results showed an accuracy of 69.1% in identifying male and females but they stated that 75% accuracy or greater was more acceptable. For future use of this model in FO, the authors recommended that the results should be tested on a larger population to take into account other factors influencing tooth development: genetics, race, socioeconomic background, attachment and use of masticatory muscles.[92] An annotated radiograph is shown in figure 8 with hard tissue landmarks and measurements.

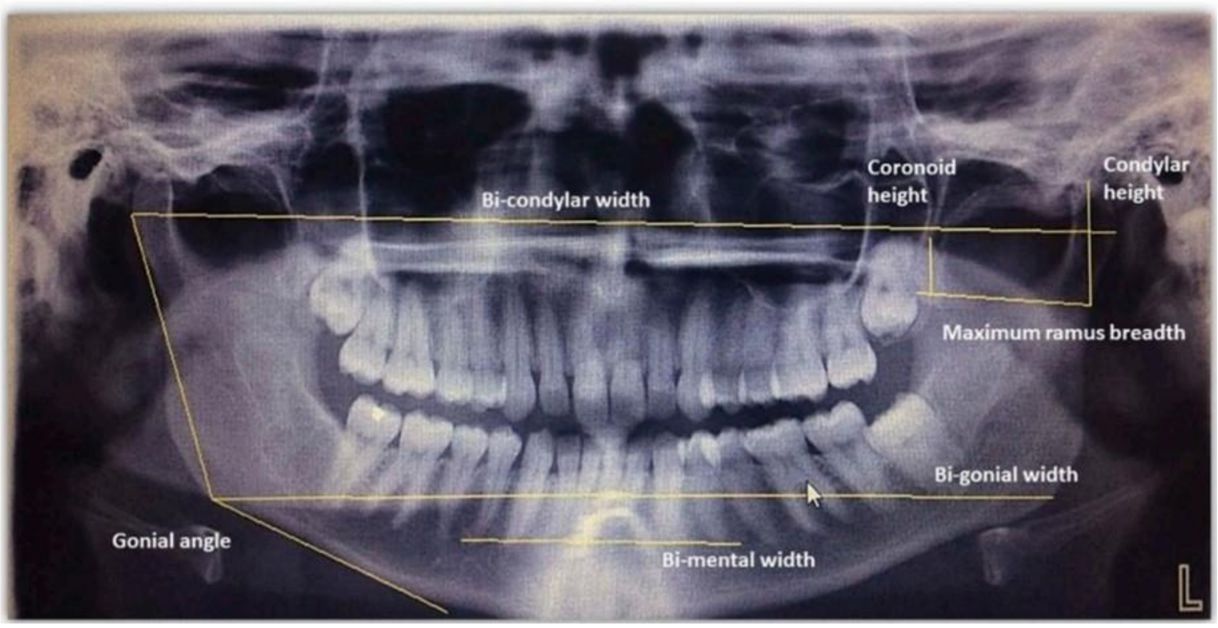

Figure 8: Measurements used for sex determination by artificial intelligence.[91]

8.6 AI in making dental identifications

Khanagar et al. (2021) used a systematic review evaluating the application and performance of AI technology in FO, stating that AI can be trained and applied for problem solving and clinical decision-making in both medical and dental fields.[89] They found the use of AI technology has been widely investigated for identifying bite-marks, predicting mandibular morphology, sex determination, and age estimation in the living and deceased. Mandibular morphology can be used for facial reconstruction for identification, sex determination and in making skeletal classifications (Class I, II, III).

The application and performance of AI has been studied in several aspects of identification by forensic odontology:

- Remains
- Teeth
- Mandible to determine sex
- Maxilla
- Eruption patterns

Models with accuracy and precision similar to that of a trained forensic odontologist, meaning that there is scope for using AI for disaster victim identification and aiding in medico-legal situations. The graph below (fig 9) shows the areas that AI is currently applied in forensic odontology.[89]

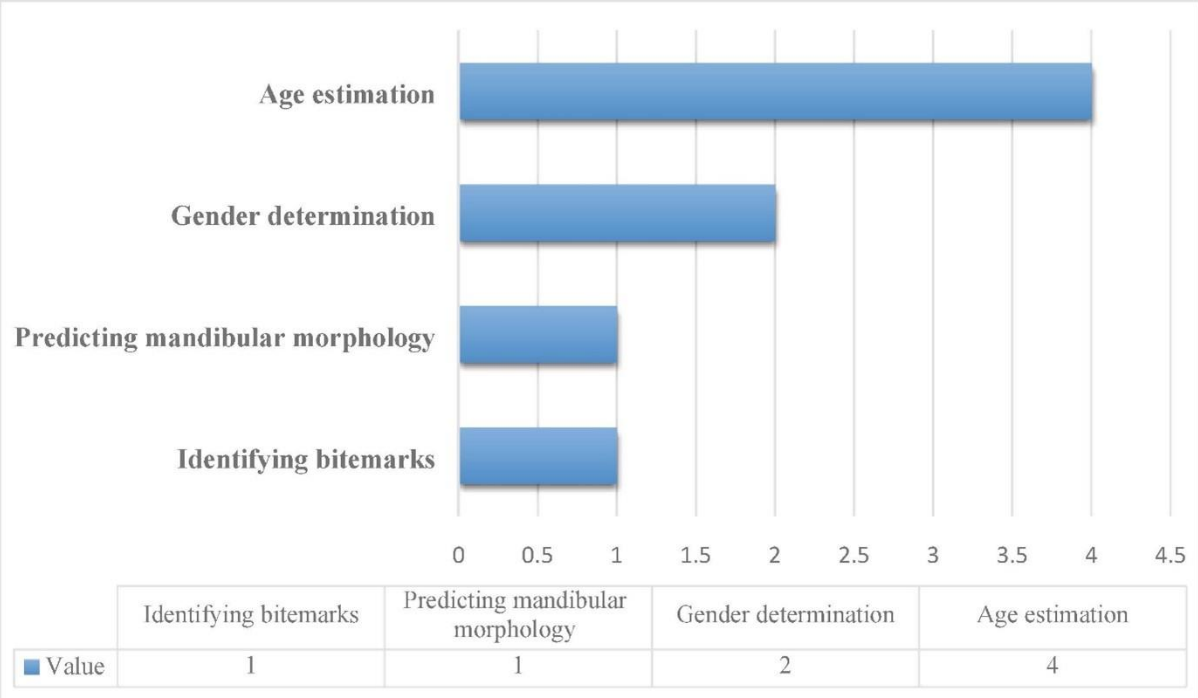

Figure 9: Use of artificial intelligence in areas of forensic odontology.[89]

Currently, age estimation is the area of FO where AI is most largely applied, followed by sex determination, mandibular morphology and identifying bitemarks. Using highly trained AI models, decision making and problem-solving can be done with excellent results. Decision making is key in FO as age estimation and sex determination rely on accurate expert opinions but an advantage of using AI is the elimination of observer bias.[89]

As DPTs are commonly used for age estimation and chronological age, this may result in more simple and reproducible training for the AI compared to training using photographs of bitemarks. For example, a DPT has a standardised size and scale and angle for all individuals, the image will be back and white, the centre of the dentition will be in the centre of the image, the anatomical structures (ramus, body of mandible, sinus, mental foramen) are seen consistently.

AI for bitemarks has been designed to identify specific features of bitemarks in wax.[93] In reality, training AI for bitemarks on human skin may prove difficult due to the many variable factors: images show many colours, shapes and patterns using different scales and with different skin tones on different areas of the body. There is great potential for AI in age estimation on radiographs and, as technology advances, in analysing all forms of evidence in forensic odontology.

Currently, most studies are preliminary, experimental in nature and don't reflect 'real life' scenarios and therefore, the success in cases is yet to be studied. Future research should conducted on use of AI in other areas of FO such as lip prints, palatal rugae, cemental lines, dentine translucency and their application to cases.[89]

9) The legal system and age estimation of accurate age estimation

9.1 Age of criminal responsibility

Legally, DAE for adolescents and young adults is implicated in the interpretation and judgment of criminal law to determine either an adult or minor status.[94, 95] This will determine whether a suspect has reached the age of criminal responsibility and whether the individual is treated under general criminal law for adults.[96]

The difference between an individual being classified as an adult or minor could determine if they are considered an adult or young offender, how they are convicted and punished,[97] their maximum penalty,[98] whether the case is sent to a criminal court and whether their name is published to the public.[97]

With regards to an individual being of the age of legal majority, Garamendi et al. (2005) noted that a more beneficial criminal treatment occurs with false negatives while a minor's rights will be violated with false positives in age estimation.[99]

Therefore, age estimation methods must keep false negatives to a minimum, but it is ethically unacceptable for false positives to occur in cases involving the criminal responsibility presumed minors.[100]

9.2 Asylum seekers

In the United States, if the age of an asylum seeker estimates that they are an adult and not a minor, they will await court hearings in Immigration and Custom Enforcement (ICE) operated jails and housed with adults rather than being placed in youth shelters.[38] This can expose them to physical harm, mental distress, depression, anxiety and post-traumatic stress disorder. The court hearing will reference the dental radiograph findings and if a minor is thought to have purposefully lied about their age, this can jeopardize the credibility of their asylum claims which and prolong their immigration proceedings for months or years while they remain in the ICE jails.

In the UK, migrants claiming to be minors receive better housing and support, access to children's services, given a more sympathetic hearing and are less likely to be detained.[101] Experts on the scientific advisory committee will look at the methods used to determine the chronological age, including X-rays and other types of radiology, CT and MRI scans. This will mean that asylum seeking adults posing as children are not given support which they are not entitled to and remove safeguarding risks of adults incorrectly placed in the children's care system.

Therefore, there are legal and financial consequences of a false positive age estimation and a "false adult" is the least desirable outcome with the greatest negative implications.

Local authorities look after children, and there are practical implications for deportation where asylum claims are rejected. Financially, in United Kingdom (UK), it was revealed that over £2 million had been paid to 40 child asylum-seekers in a court settlement who were wrongly detained as adults from flaws in the age assessment process.[100] This highlights the importance of legal representatives fully understanding the age assessment process, and the medical practices involved in determining if an individual is a minor.

9.3 Missing persons search

If a cadaver is estimated with an age that is incorrect, this can lead to missing persons being excluded.[8] For example, if an estimated age range is 30-45 years but the missing person is 47, this excludes the missing person and the age estimation hinders a positive identification.

10) Age estimation of sixteen

10.1 Sports

The "National Code against Age Fraud in Sports" report states that an age estimation will include radiographic DAE using DPTs and a medical examination using hand–wrist radiograph and/or CT scans.[102] Similarly, hand–wrist radiographs (Tanner Whitehouse – TW3 method) are used by the Board of Control for Cricket in India, where age fraud is particularly prevalent, for age estimation in players competing in under 16 categories.[103]

There are various reasons why this is such a problem in India: it is acceptable among parents and there is a culture, and even appreciation of jugaad, and fake documents can be easily obtained.[104] The National Inter-District Junior Athletics Meet (NIDJAM) in Tirupati, India held in 2019 experienced rampant age fraud.[105] Some 51 athletes were declared to be overage from DAE and TW3 procedures and 65 athletes did not complete their TW3 tests after they attended for their dental examination.

10.2 Legal age of consent

Although the age of consent worldwide ranges from 12 to 21 years old, many have 16 as the age of consent: Singapore, Indonesia, Cuba, Ukraine, Belgium, Netherlands, Switzerland, Finland and Norway.[106]

Accurate age estimation is just as important for females as it is for males: The UK National Society for the Prevention of Cruelty to Children (NSPCC) found that over a third of all police-recorded sexual offences were against children and that girls and older children are more likely to experience sexual abuse.[107] When a girl aged 13 is found to be pregnant, consideration should be given to the age of conception. If the age of conception is under 13 years, this would be a considered statutory rape and a referral must be made to the First Contact and the case reported to the Police.[108] Although most births are registered in the UK, in many countries there is a lack of birth records and therefore proof of age.

In the UK, young people under the age of 18 are offered protection under the Children Act 1989.[109] Young people over the age of 16 and under the age of 18 are not deemed able to give consent if the sexual activity is with an adult in a position of trust or a family member as defined by Part 5 of the Sexual Offences (Scotland) Act 2009[110] and attention should be paid to sexual exploitation and the abuse of power.[111]

There may be discrepancies in how old a minor is for consent. Either the minor may have lied about their age, or a perpetrator may claim that a victim of sexual assault had lied but in either case, adults who engage in sexual activity with a minor can be charged with a sex crime as the minor cannot legally consent.[112]

10.3 Abortion

The age of a victim may be important for legal abortions as a result of sex without consent. For example, the Penal Code, adopted in 1979, states that an abortion is considered illegal only if it is without the consent of the pregnant woman, is unsafe, or is provided for profit.[113]

According to the Moroccan Family Planning Association, abortions should be permitted within the first three months if the woman's physical and mental health is in danger, in cases of rape, incest, or congenital malformation. However, unmarried women would be excluded from the criteria because having sex outside marriage is illegal.[114]

There are many countries where abortion is illegal: Honduras, Egypt, Iraq, Malta, Philippines, Palau, Madagascar, Laos, Jamaica, Haiti, El Salvador, Senegal, Sierra Leone and the Dominican Republic.[115] In other countries such as Brazil, abortion is illegal except in cases of rape, foetal anencephaly or if the pregnancy poses a risk to the woman's life. The ability to access legal and safe abortions is limited which can lead to serious health complications.[116]

10.4 Marriage

The number of children involved in age disputes is increasing, and those cases are seen mostly in cases of child labour and child marriage, impacting children's education, physical and psychological health.[117] For example, in Afghanistan UNICEF released a statement saying:

> "as most teenage girls are still not allowed to go back to school, the risk of child marriage is now even higher. Education is often the best protection against negative coping mechanisms such as child marriage and child labour."[118]

Age estimation research is particularly important in India due to previously mentioned poor birth registration practices and issues relating to child rights, making safeguarding the rights of children who lack birth records and those involved in falsified age claims difficult.[39] Forensic odontologists and other forensic experts in DAE must move forward to reach a universal consensus on age estimation which will involve input from public health authorities, law enforcement agencies, social workers, and stakeholders to secure the rights of vulnerable children. In addition to the estimation of age, the likelihood of a child being over or under a specific age threshold should be calculated.[119]

Other areas of age estimation not discussed in detail are becoming employed and join the army.[7]

Aims for this study

1. To investigate if artificial intelligence (AI) can predict whether an individual is under or over 16 based on their lower left mandibular third molar on a dental panoramic tomography radiograph.

2. To evaluate how accurate the AI is at correctly classifying images in the context of dental age estimation.

3. To compare the performance of the AI in estimating the dental of age males and females.

Chapter 2: Material and methods

11) Research design

11.1 Ethical aspects and study design

This study was performed under the approval of the local committee of ethics in human research. The Declaration of Helsinki (DoH), 2013, was followed to assure ethical standards in this medical research.[120] As this was a diagnostic study using retrospective sample collection, the sample was collected from a pre-existing institutional image database to feed machine learning within the context of AI.

The radiographs were taken clinically as part of orthodontic treatment prior to this study so no patients were exposed to ionising radiation for research purposes.

11.2 Sample and participants

The sample consisted of dental panoramic radiographs from Brazilian individuals used for training (n = 4200; 2100 males and 2100 females) between the age of 6 and 22.9 years and was obtained from a private oral imaging company in Brazil.

Exclusion criteria included radiographs without patient information on sex, date of birth and date of image acquisition. The images did not contain dental implants; visible bone pathology and anatomic deformity; extensive restorations; severely displaced and/or supernumerary teeth. The images were uploaded and analysed on a 75 Elitebook 15.6” FHD Laptop with i5 (Hewlett-Packard, Palo Alto, CA, USA). Annotations were performed using the Darwin V7 software package (fig 10).

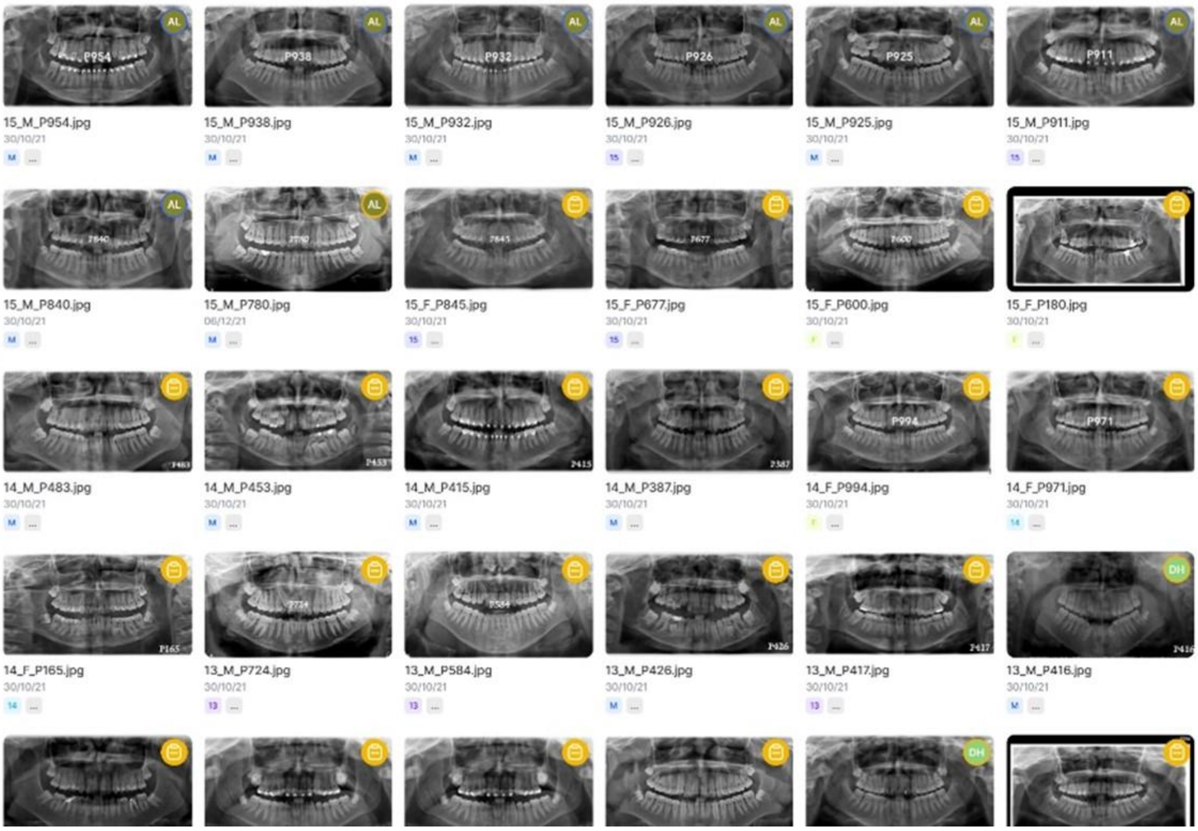

Figure 10: Sample of images showing age and sex.

11.3 Annotations and pre-processing radiographs

Three trained observers with experience in forensic odontology performed annotations supervised by a forensic odontologist with 11 years of experience. The images were annotated in an anonymised way, hiding age and sex information from the operators. The software registered the annotations that were later tested for association with age.

Annotations included a bounding-box tool to select three regions of interest: ALL, LS and T38P.

11.3.1 ALL

The bounding box labelled ALL was created to contain all features of the dentition. Vertically, the y-axis covered the apical region of the most superior and inferior teeth. Laterally, the x-axis of the ALL bounding box included the left and right third molars.

11.3.2 LS

Another box was made to cover the left side of the patient's dentition, labelled LS (fig 11).

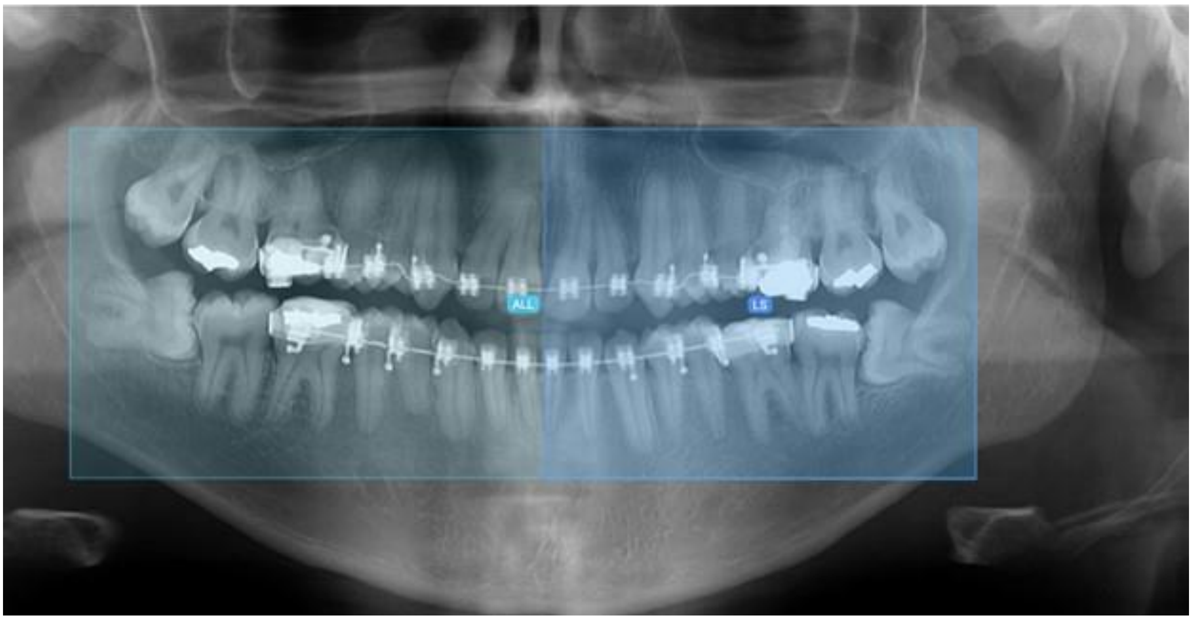

Figure 11: ALL bounding box showing the whole dentition and LS bounding box containing left side of the dentition only.

11.3.3 T38P

The mandibular third molar was selected using an automatic annotation tool by creating individual points around the tooth which could manually be altered individually to accurately outline the tooth (fig 12).

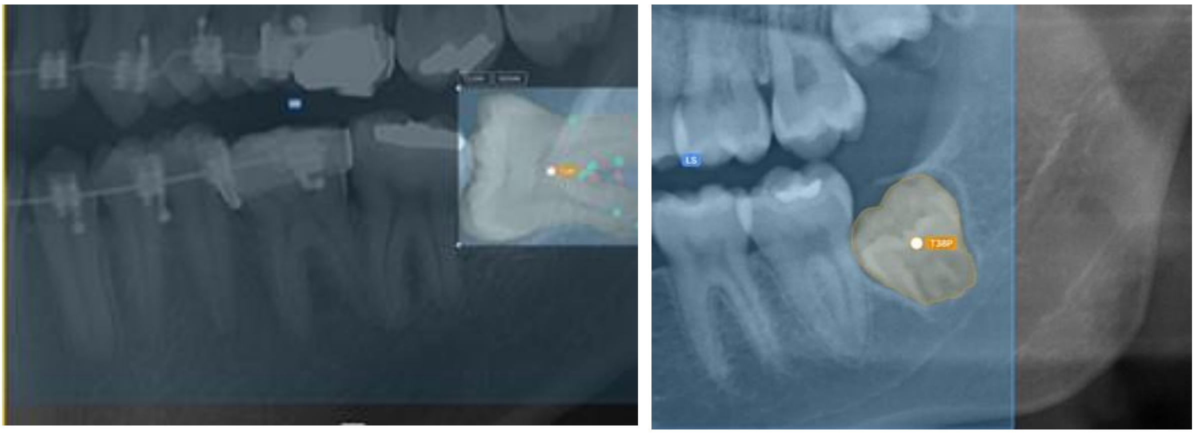

Figure 12: Auto-annotation of lower left third molar.

Each annotated radiograph included 3 labels ALL, LS and T38P (fig 13) .

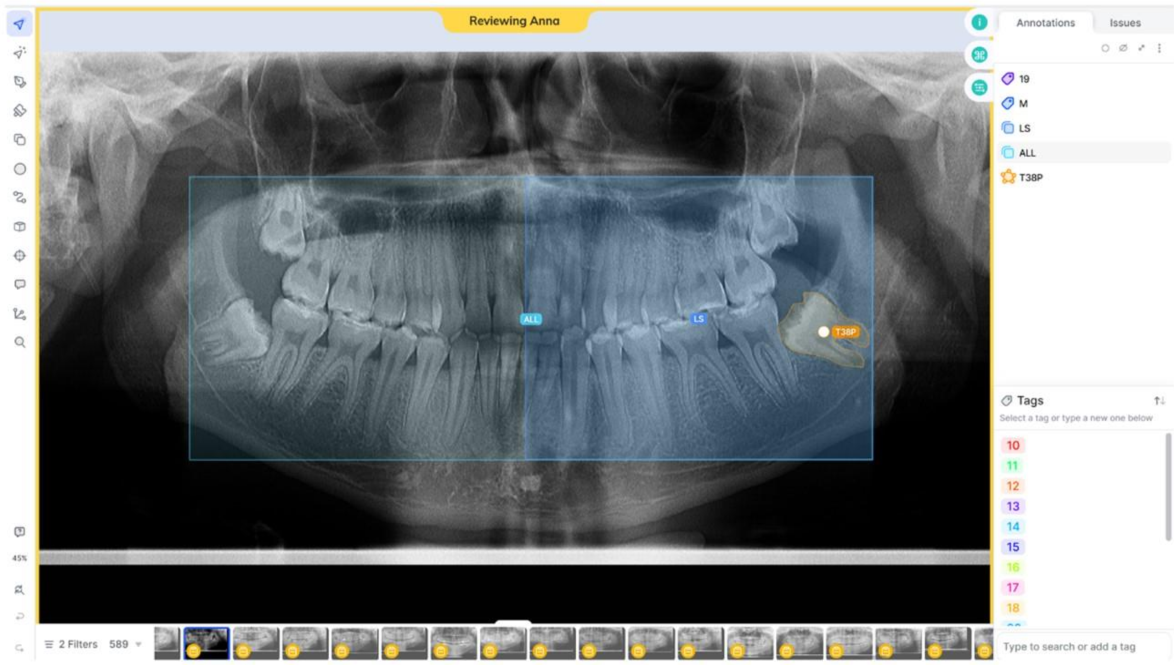

Figure 13: Computer screenshot of annotated image showing lower left third molar (38) highlighted

11.4 Classification of images

The full dataset of annotated DPTs was classified into male and female based on the image file name containing the individual's sex and date of birth.

Table 1 presents the summary of the number of radiographs used in both the training and validation of the DenseNet121 software. The total sample of radiographs (equal or above 16 years) for training and validation was (n=5040).

Table 1: Number of images used in training and validation.

Training	**Validation**
Females Under 16: 840 Over 16: 840	Females Under 16: 210 Over 16: 210
Female total: 1680	Female total: 420
Males Under 16: 840 Over 16: 840	Males Under 16: 210 Over 16: 210
Male total: 1680	Male total: 420
Total: 4200	**Total: 840**

The images were pre-processed preserving a high level of detail and signal-to-noise ratio while avoiding geometric distortion and photometric nonlinearity. Additionally, the region within the ALL-bounding box was used to centralise the teeth in the input images for further neural network training.

11.5 CNN architecture and training

DenseNet121 software is currently one of the most successful models and is available from open sources (e.g. TensorFlow1 and Keras API2). Additionally, DenseNet121 outperformed other architecture models in a pilot study carried out by Franco et al. (2022) comparing seven other models and their decision-making process in a study using AI for investigating dental sexual dimorphism in DPTs.[121] Table 2 shows the network's characteristics.

Table 2: Metrics used in evaluating the performance of the CNN.

Model	Size	Parameters	Depth	Image Size (H×W)	Hyper parameters				
					Optimization algorithm	Batch Size	Momentum	Weight decay	Learning Rate
DenseNet121	33 MB	8,062,504	121	224×224	SGD	32	0.9	1e-5 ~ 1e-6	Base lr=0.001 Max lr=0.00006 Step size = 100 Mode = triangular

In this work, DenseNet121 was trained with two approaches: From Scratch (FS) and Transfer Learning (TL).

11.5.1 From Scratch

From Scratch (FS) is the learning process to train the machine, beginning with no knowledge and learning to recognise the teeth and patterns in the radiographs. With FS learning, the network weights (which take the input signals and pass the relevance of the input to the next layer of processing) are randomly initialised.

Overfitting is where the model categorises the training set to the point that there is little or no room for generalisation of new data, meaning that results will show greater errors with new or unfamiliar testing data.[122] FS requires a larger training set which increases the risk of overfitting and there is a risk that the criteria are too specific for accurate categorisation. Conversely, underfitting is too generalised (fig 14).

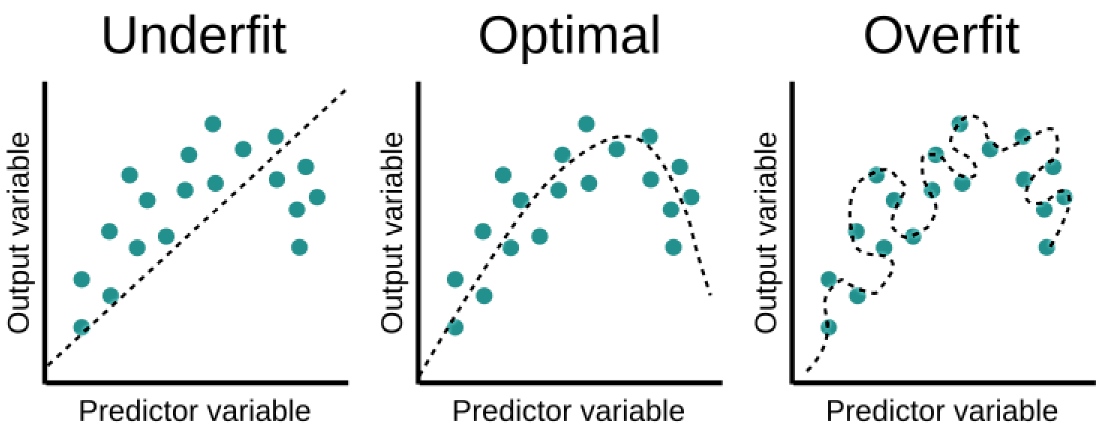

Figure 14: Comparison of underfitting, optimal fitting and overfitting.[123]

Since the network had no previous training, the software relied on the input data to define all inherent weights which allowed a problem-specific network topology that could improve the overall performance.

To avoid overfitting and therefore improve the generalisability of the evaluated models, a computational framework, Keras,[124] was used for pre-processing layers to create a series of image data augmentation layers which produced pre-processing code (which can be used in non-Keras workflows). These layers were only used during the training stages which applied random augmentation transformations to the image sample.

11.5.2 Transfer Learning

The second learning approach was Transfer Learning (TL) where the machine processes the images from existing knowledge through a more mature learning process than FS. The TL method utilises previous weights as foundation to develop and be applied to a new domain of interest. Labelled data is borrowed, and knowledge extracted from related fields to obtain an improved performance within the bounding boxes.

TL can be applied using a base neural network as a fixed feature extractor. The images of the target dataset were fed to the deep neural network and the features of the radiographs were recognised by the software as important for categorising images and generated as input to the final classifier layer and to be extracted.

Through these features, a new classifier is built, and the model is created using important input information from the radiographs to make the classification. The base network (in the last layer of the classifier) had a fine-tuning strategy added, and the weights of previous layers were also modified. Pre-trained weights were used based on the ImageNet model and implemented transfer learning to best-fit the dataset (fig 15, 16).

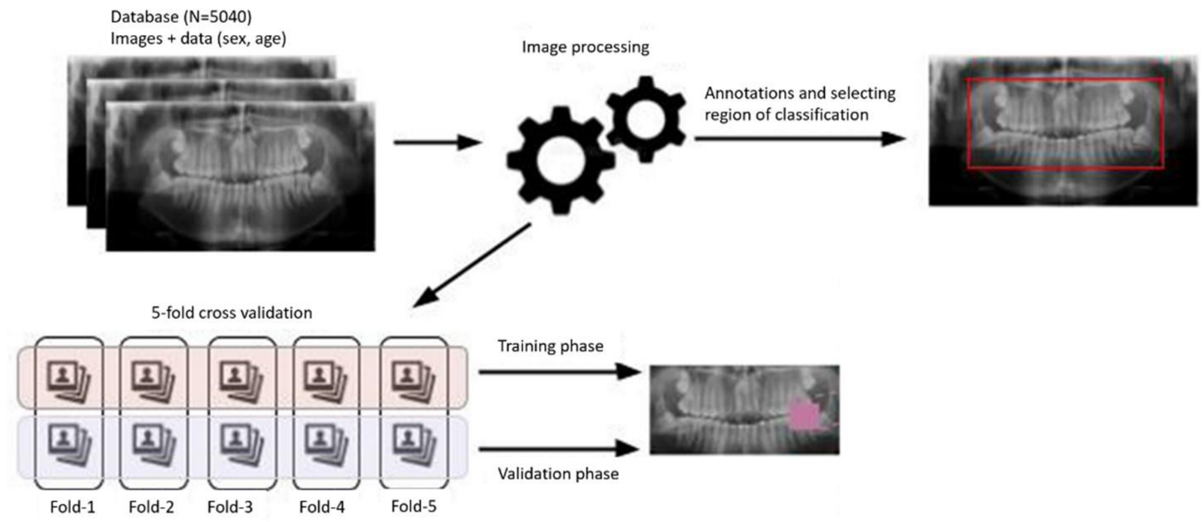

Figure 15: Image processing and validation and train weights to recognise patterns in the lower left third molar.

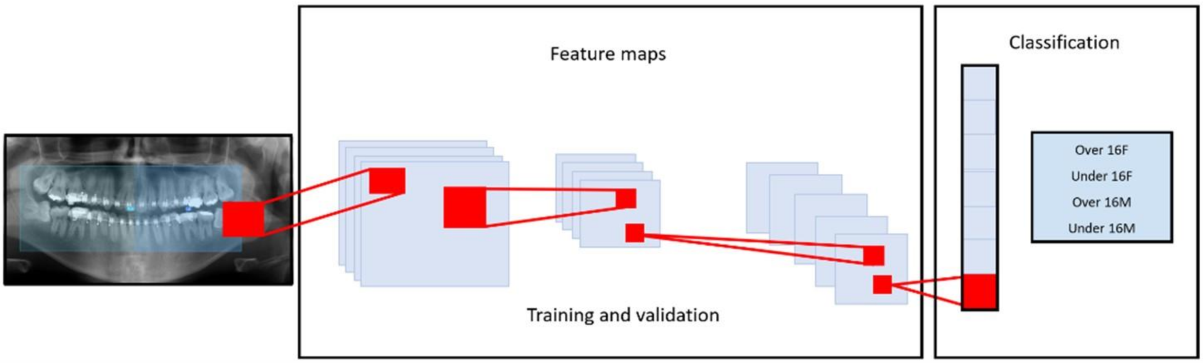

Figure 16: Model structure showing the workflow from sampling, image processing, annotation, cross-validation, training/validation to classification.

Table 3 presents each layer and the respective implemented parameters. Accordingly, the training cross-validation approach used a ratio of 80:20 120 for the sample respectively. The ratio was dynamic over five repetitions for each of the architectures (TL and FS) so that all the training samples had a different dataset built (randomly selected) from the original sample. Importantly, none of the images used during the training process were used in the validation stage.

Table 3: Layers and parameters for processing and categorising images.

Layer	Parameter
RandomTranslation	height_factor=0.1, width_factor=0.1, fill_mode='reflect'
RandomFlip	mode='horizontal_and_vertical'
RandomRotation	factor=0.1, fill_mode='reflect', interpolation='bilinear'
RandomContrast	factor=0.1

A stochastic optimisation algorithm (SGD) was used for optimisation in training the proposed network. Initially, a base learning rate of 1×10^{-3} was set and this was then decreased to 6×10^{-6} with increased iterations.

In the validation process, a k-fold cross-validation method was used. The dataset was divided into 5 (k) mutually exclusive subsets of the same size. This strategy caused a subset to be used for the tests and the remaining $k - 1$ was used to estimate the parameters to compute the accuracy of the model.

11.6 Performance Metrics

To evaluate the (radio-diagnostic) classification performance of the AI, there were several metrics which could be altered to determine accuracy performance metrics.

In the training stage, the internal weights of the model were updated during several iterations. Each iteration in the training period was supervised, saving the weights with the best predictive power of the model determined by the overall accuracy metric.

Table 4 shows how the metrics are calculated, giving measurements to assess the performance of the AI machine. The accuracy gives the overall performance along with other figures and considers the specifications of the computer.

Table 4: Metrics to analyse results.

Metric	Formula	Evaluation focus
Loss	$L\left(\hat{y_i}, y_i\right) = -\sum_{i=1}^{k} y_i \cdot log\left(\hat{y_i}\right)$	A loss function is a method of evaluating how well the model the dataset. The loss function will output a higher number if the predictions are off the actual target values whereas otherwise it will output a lower number. Since our problem is of type multi-class classification we will be using cross entropy as our loss function.
Accuracy	$\sum_{i=1}^{k} \frac{tp_i + tn_i}{tp_i + tn_i + fp_i + fn_i}$	The accuracy of a machine learning classification algorithm is one way to measure how often the algorithm classifies a data point correctly. Number of items correctly identified as either truly positive or truly negative out of the total number of items.
F_1-score	$2 * \frac{Precision * Recall}{Precision + Recall}$	The harmonic average of the precision and recall, it measures the effectiveness of identification when just as much importance is given to recall as to precision.
Precision	$\frac{\sum_{i=1}^{k} tp_i}{\sum_{i=1}^{k} (tp_i + fp_i)}$	Agreement of the true class labels with those of the classifier's, calculated by summing all TP's and FP's in the system, across all classes.
Recall	$\frac{\sum_{i=1}^{k} tp_i}{\sum_{i=1}^{k} (tp_i + fn_i)}$	Effectiveness of a classifier to identify class labels, calculated by summing all TP's and FN's in the system, across all classes.
Specificity	$\frac{\sum_{i=1}^{k} tn_i}{\sum_{i=1}^{k} (tn_i + fp_i)}$	Specificity is known as the True Negative Rate. This function calculates the proportion of actual negative cases that have gotten predicted as negative by our model.

k = total number of classes; tp = true positives; fp = false positives; tn = true negatives; fn = false negatives

11.7 Confusion matrix

A confusion matrix contains information about actual (real) and predicted classifications accomplished by a classification system. Figure 22 shows how the performance of the implemented architectures was evaluated using the matrix data.

Figure 17: Confusion matrix decision making process.[125]

A confusion matrix is often utilised with two classes: the positive class and the negative class and divided further into four cells of the matrix: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).

This approach helps to identify and reduce bias and variance problems and enables adjustments capable of producing more accurate results. The confusion matrix can be denoted as in equation 1 where $RR_{i,j}$ corresponds to the total number of entities in class C_i which have been classified in class C_j. Hence, the main diagonal elements indicate the total number of samples in class C_i correctly recognised by the system (fig 18):

$$CM = \begin{bmatrix} RR_{1,1} & RR_{1,2} & \cdots & RR_{1,N} \\ \vdots & \vdots & & \vdots \\ RR_{2,1} & RR_{2,2} & \cdots & RR_{2,N} \\ \vdots & \vdots & & \vdots \\ RR_{N,1} & RR_{N,2} & \cdots & RR_{N,N} \end{bmatrix}$$

Figure 18: confusion matrix equation.

11.8 Receiver Operating Characteristic curve

The receiver operating characteristic curve (ROC) analyses the performance of classification systems.[126] High true positive rates (TPR or sensitivity) of a class indicate that the model has performed well in that classification. ROC curves can be compared for various models, and the model with the highest area under the curve (AUC) is considered to have the best performance. This is a common metric approach in AI to assess diagnostic data.

11.9 Software and Hardware System Description

The experiments were imported to a Linux machine, with Ubuntu 20.04, an Intel® Core(TM) 155 i7-6800K processor, 2 Nvidia® GTX Titan Xp 12GB GPUs, and 64GB of DDR4 RAM. All models were developed using TensorFlow API version 2.5 and Keras version 2.5. Python 3.8.10 was used for algorithm implementation and data wrangling.

12) Results

The results showed that the AI could categorise DPTs into 2 categories using the annotated lower left third molar: under 16 and over 16. A confusion matrix for binary classification shows the four different outcomes: true positive, false positive, true negative, and false negative (fig. 19). These outcomes were used to calculate precision and recall based on the true and predicted labels.

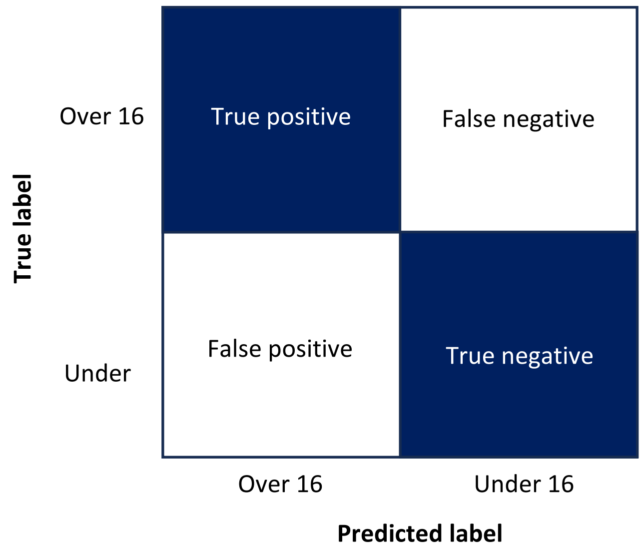

Figure 19: Confusion matrix showing four outcomes.

Male confusion matrix

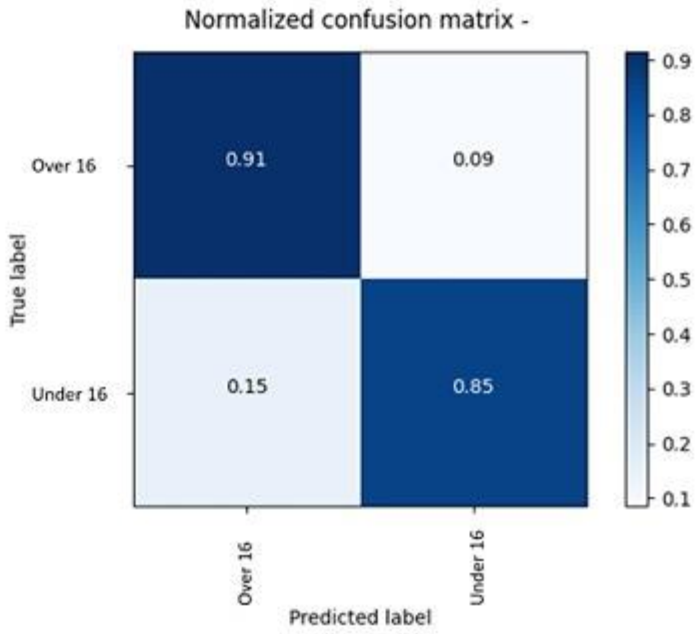

Figure 20: male confusion matrix.

The Y-axis shows the true positive results (verified from the individual's date of birth) and the X-axis shows the prediction by the AI. Results for the male $DPT_{>16}$ were correctly classified 91% of the time and 85% of the time for $DPT_{<16}$ (fig 20). This gives a high true positive rate and therefore high accuracy of classification. The error rate of false negatives was 0.15 and the rate of false positives was 0.19.

The AI was more likely to correctly classify $DPT_{>16}$ than $DPT_{<16}$ with a slightly lower error rate for $DPT_{<16}$.

Female confusion matrix

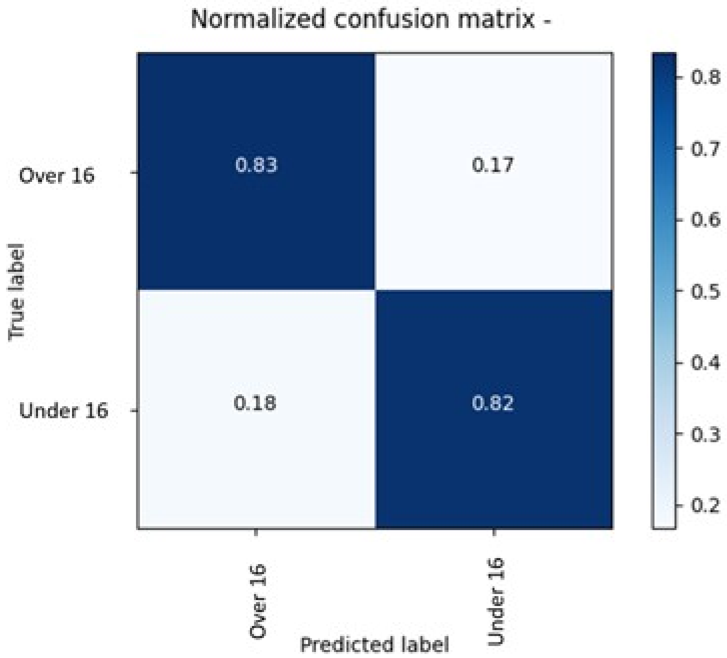

Figure 21: Female confusion matrix.

Females had a true positive rate of 83% for DPT $_{>16}$ and 82% for DPT$_{<16}$ (fig 21). Similar to males, this gives a high true positive rate and therefore high accuracy of classification. However, females had a much higher false positive rate of 0.17 for DPT$_{<16}$ and a higher false negative rate of 0.18 for DPT$_{>16}$. In females, the AI was more likely to correctly classify DPTs as over 16 than under 16, with a slightly lower error rate for under 16.

12.1 Accuracy

Accuracy is simply the number of data points that were correctly classified (as true positive or true negative) from the sample: how many DPTs were correctly classified out of all the DPTs in the sample?

Accuracy for males

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Accuracy = \frac{0.91 + 0.85}{0.91 + 0.09 + 0.85 + 0.15}$$

$$Accuracy = 0.88$$

Accuracy for females

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Accuracy = \frac{0.83 + 0.82}{0.83 + 0.17 + 0.82 + 0.18}$$

$$Accuracy = 0.83$$

Therefore, accuracy for males was higher than for females.

12.2 Precision

Precision is the proportion of positive results that were correctly classified to express the proportion of the data points our model says existed in the relevant class that were indeed relevant: of all the DPTs classified by the AI as being over 16, how many true positives were correct?

The highest precision score would be 1.0 and lowest 0.0. Therefore with a score of 0.91, 91% of males were calculated with high precision compared to a precision of 83% in females.

Precision for males

$$Precision = \frac{TP}{TP + FP}$$

$$Precision = \frac{0.91}{0.91 + 0.09}$$

$$Precision = 0.91$$

Precision for females

$$Precision = \frac{TP}{TP + FP}$$

$$Precision = \frac{0.83}{0.83 + 0.17}$$

$$Precision = 0.83$$

The metric with the largest difference between males and females was precision, meaning that more females were classified as being over 16 when they were, in fact, under 16. The proportion of true positive male over 16 DPTs correctly classified was higher and, out of the sample, the males had less false positives than females.

12.3 Recall (sensitivity)

Recall shows the number of samples predicted correctly to be belonging to the positive class out of those truly belonging to the positive class, or more simply, the true positive rate.

Male recall

$$Recall = \frac{TP}{TP + FN}$$

$$Recall = \frac{0.91}{0.91 + 0.15}$$

$$Recall = 0.86$$

Female recall

$$Recall = \frac{TP}{TP + FN}$$

$$Recall = \frac{0.83}{0.83 + 0.18}$$

$$Recall = 0.82$$

As the recall increases, the precision decreases: instead of every sample being assigned as a true positive, the recall will start to classify only samples which are truly positive. A very high recall would give no precision because there would be no false positives. For this reason, both precision and recall are important.

In the area of DAE, the metric which is more useful may be precision rather than recall because recall will classify all possible over 16's with less accuracy, whereas precision would be more selective and the output would be more accurate. This would mean that more of the predicted over 16's would indeed be over 16 but many borderline DPTs would be left and labelled as under 16.

12.4 F1 score

F1 takes into account both precision and recall. A high F1 score means that the AI is able to predict both true positives and true negatives.

Male F1 score

$$F1\ Score = \frac{2 \times precision \times recall}{precision + recall}$$

$$F1\ score = \frac{2 \times 0.91 \times 0.86}{0.91 + 0.86}$$

$$F1\ score = 0.88$$

Female F1 score

$$F1\ Score = \frac{2 \times precision \ \times recall}{precision + recall}$$

$$F1\ score = \frac{2 \times 0.83 \times 0.82}{0.83 + 0.82}$$

$$F1\ score = 0.82$$

12.5 Specificity

Specificity is the number of samples predicted correctly to be in the negative class out of all the negative classes, similar to precision but for true negative predictions rather than true positives: of the under 16 DPTs in the sample, how many were correctly classified?

Male specificity

$$Specificity = \frac{TN}{FP + TN}$$

$$Specificity = \frac{0.85}{0.09 + 0.85}$$

$$Specificity = 0.90$$

Female specificity

$$Specificity = \frac{TN}{FP + TN}$$

$$Specificity = \frac{0.82}{0.17 + 0.82}$$

$Specificity = 0.83$

Females had a lower specificity, meaning that the likelihood of the AI categorising the $DPT_{<16}$ correctly is less likely for females than males therefore, there is less likelihood of a true negative in females.

The most important aspect of the confusion matrix is the X-axis showing the false positive rate because, when a false positive occurs an individual is classified as being over 16 when they are, in fact, a minor.

12.6 Area under the curve (ROC)

Finally, area under the curve graphs were made for males and females which summarise all the previous metrics to analyse the data. A high area under the curve represents both high recall and high precision (high precision means a low false positive rate, and high recall means a low false negative rate.

Male ROC

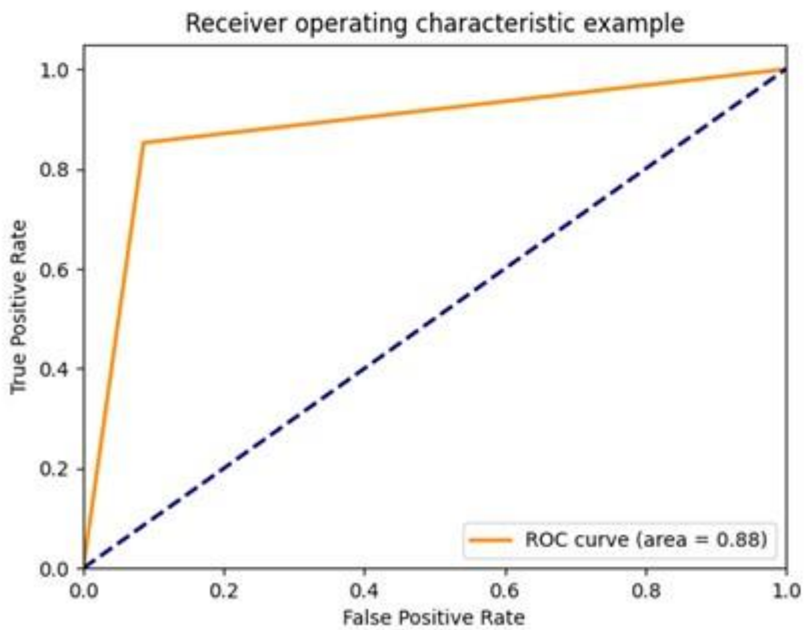

Figure 22: Area under the curve for males

The ROC was 0.88 meaning that the accuracy of the AI for males was 88% (fig 22).

Female ROC

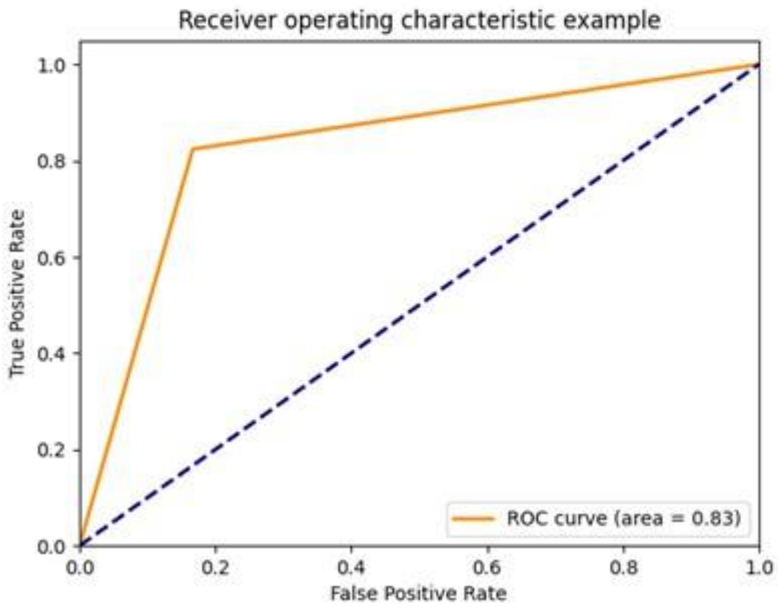

Figure 23: Area under the curve for females

The area under the curve was 0.88 meaning that the accuracy of the AI for females was lower than males at 83% (fig 23).

In summary, the AI could classify the DPTs into over and under 16 with males with a higher overall accuracy than females, who had more false positives than males.

Discussion

13) Exclusion criteria and population

In this study, exclusion criteria did not include the presence of orthodontic brackets, wires and other appliances which did not seem to affect the performance of the AI, although there were many lower third molars which were partially erupted, impacted or not included in the fixed appliances.

Other studies investigating DAE radiographically using third molars will also exclude radiographs showing variations in tooth eruption or morphology, and a history of medical disease or surgical intervention that could affect the presence and development of third molars[127,128,129]

One limitation of our study is that no information was collected on the ethnic and socioeconomic status or medical history affecting dental development in this study. Evidence shows a significant variability in dental development based on race and ethnicity, sex, socioeconomic status, systemic disease, nutritional health, and other environmental factors.[130]

13.1 Socioeconomic status

All maturational changes happen in a uniform way for most individuals but the timing of these changes are the important factor for age assessment. Differences in the timing of maturation between males and females has been well documented, but there are many other factors that can impact this timing, such as socioeconomic factors.[131] The DPTs in this study were from a private orthodontic clinic in Brazil so it is reasonable to assume that the individuals being treated here would have above average income.

During their examination of social inequalities and oral health, Boyce et al. (2010) found higher levels of cortisol secretion in children of lower socioeconomic status.[132]

Cortisol reactivity has been linked to harmful changes in enamel which may cause microanatomical defects.[133] The results of these studies suggest that higher levels of stress hormones may also be responsible for the observed differences in dental development.

By considering the biological mechanisms and pathways in dental development, there is the opportunity to understand how tooth formation responds to the biocultural influences present in an individual's environment. This knowledge can improve interpretation of sociocultural circumstances through analysis of the dentition and make more appropriate methodological decisions about age estimation.[133]

Therefore, when applying age estimation methods to refugees and asylum seekers, the low socioeconomic status and malnutrition that are often related to refugee status can delay skeletal maturation.[134,135] Additionally, concurrent diseases often delay dental development which are common features for refugees and other individuals who require age estimation.[135] For example, Singh et al. (2008) found that refugee torture survivors to the United States had commonly experienced poor nutrition and lack of medical or dental care, affecting their oral health status which was then exacerbated by the conditions in refugee camps: overcrowding, violence and stress.[136] Therefore, it is important for AI methods to include individuals of lower socioeconomic status to test and improve its accuracy to take into account the possible variability in development.

13.2 Ethnicity

13.2.1 Third molar variation

The UK Home Office have reported that there is considerable variability in third molars between ethnic groups.[137] The level of dental development was compared across several populations, finding that the youngest individuals reached maturity when they were under 17 in American Hispanics whereas, in Thailand, they had reached maturity once they were over 17. Furthermore, by age 18, the proportions of individuals with mature third molars varied ten-fold from 3% to 30%. The age at which 50% of individuals reached maturity ranged from 18.7 years in Chile to 20.8 years in Thailand, a full two years later. Therefore, further methods of using AI for DAE on third molars should be carried out on different populations so that population-specific standards can be used to enhance the accuracy of forensic age estimates based on wisdom tooth mineralisation in living subjects.[138]

The ethnicity of the individuals used in this study is unknown, however, the radiographs were from the state of Goiás, the central-west region of Brazil. The Continuous National Household Sample Survey (PNAD) from 2021 showed that Goiás demographics include Pardo People (58.2%), White People (33.3%), Black People (7.8%) and Asians & Amerindians (0.7%). This region has a strong white background and more north African descents but has received migrants from all parts of Brazil.[139]

Jayarman suggested testing the accuracy of DAE methods on varying ethnicities rather than geographic locations because a population within a geographical boundary can contain different ethnic groups. They suggest that this could be done by tracing family trees to develop a classification system.[53]

Gorgani et al. (1990) examined 229 black and 221 white US citizens aged 6–14 years and found Black subjects' crown mineralisation of the third molars was completed 1 year earlier.[140] Harris and McKee[141] studied 655 white and 335 black US citizens aged 3.5–13 years and found that Black subjects reached the earlier stages of wisdom tooth mineralisation around 1 year earlier although the gap appeared to narrow for later stages.

Therefore, testing DAE methods in diverse samples is needed to address the problem of uncertainty when a method is applied to an individual originating from a population that differs from the one which was used in the development of the method. When applying DAE methods and when investigating AI to apply the stages, there are other variations to consider such as the study size, distribution of sample, inter-individuality, reliability of examiner, scoring criteria and statistical analyses.

13.2.2 Ethnicity compared to socioeconomic status

Schmeling et al. (2000) investigated the effects of ethnicity on skeletal maturation in relation to forensic age estimation, with "ethnicity" defined by genealogical relationships.[142] It was concluded that skeletal maturation takes place in phases which are identically defined for all ethnic groups and that reaching those stages of skeletal maturation within the relevant age group appeared to be unaffected by ethnic identity. When considering both ethnicity and socioeconomic status, it was concluded that the socio-economic status of a given population is of decisive importance to the rate of ossification.

13.3 Populations of samples for AI research

This is the first study known to use AI for third molars of a Brazilian population for DAE. Previous DAE studies with AI have been conducted on DPTs of several populations: Spanish Caucasian,[87] Eastern Chinese,[143,144] Taiwanese,[145] Korean,[146] Korean using first molars,[147] Thai,[54] Indian,[148] Japanese,[149] Northern Chinese,[150,151,152] Bayesian populations using third molars,[6] Malaysian Indian,[153] Malaysian.[154,155] Several other studies did not include the sample population. The most data is on Asian populations so more data is needed for European and South American populations and the sample population should be included in future research publications.

Additionally, patient data should be anonymised to protect patient confidentiality before being used in AI models and systems should be adapted for this purpose.

14) Third molar development and variability

14.1 Third molar variability globally

As previously mentioned, it is well known that third molars are one of the most developmentally variable teeth in the dentition,[156] however, as they are often the only teeth developing in late adolescence and early adulthood, they may be the only tooth to rely upon which +or- 18 years of age can be verified. Reportedly, AI models are not fully developed enough to be implemented, due to their high variability when applied for the key chronological age of 18 years.[87]

Third molar variability was analysed by the American Board of Forensic Odontology (ABFO) where they conducted a study of third molar development and concluded that development can continue up until the age of 30.[157] They used Demirjian's method to compare development and significant age differences were found between the South African and Japanese samples for both sexes and that South African subjects were approximately 1–4 years younger than the Japanese subjects upon reaching later root development stages.

Statistically significant differences between German and Japanese males and between Japanese and German females, meaning that Japanese males and females were approximately 1–2 years older than their German counterparts.

The AI may be accurate with one population, but implementation on many populations and ethnicities may present challenges so further AI studies on more populations are required to overcome the difference in rates of development if methods are to be used in practice.

Another limitation of this study was the age range being 6-22.9 years. Third molars are not usually calcified until around age 8-9 years so perhaps this age range was too wide. Only annotated third molars were used to train and validate the AI so any irrelevant images or those showing third molar agenesis were not used in training or validation of the network. The age of 22.9 years may have been useful, however, because of the variability in third molar development, where differences in development can be several years.

14.2 Rates of missing lower third molars

A potential drawback of DAE using lower third molars is not only the variation, but the high incidence of tooth agenesis which is mostly affected by genetic variation[158] from mutations affecting heredity factors.[159] Third molar agenesis varies between populations, from nearly 100% of Mexican Indians having missing third molars to almost no agenesis in Tasmanian populations.

Lower left third molars were more commonly missing in females than males but interestingly, there was not a significant difference for lower right third molars between male and female.[160] Bindayel's study (fig 30) investigated the global prevalence of third molar agenesis, with the highest being Bangladesh with and the lowest being Canada with 9.7%. The British population had a prevalence of 12.7% prevalence of third molar agenesis, 24.7% in the Chile population and 41% for the Korean population.

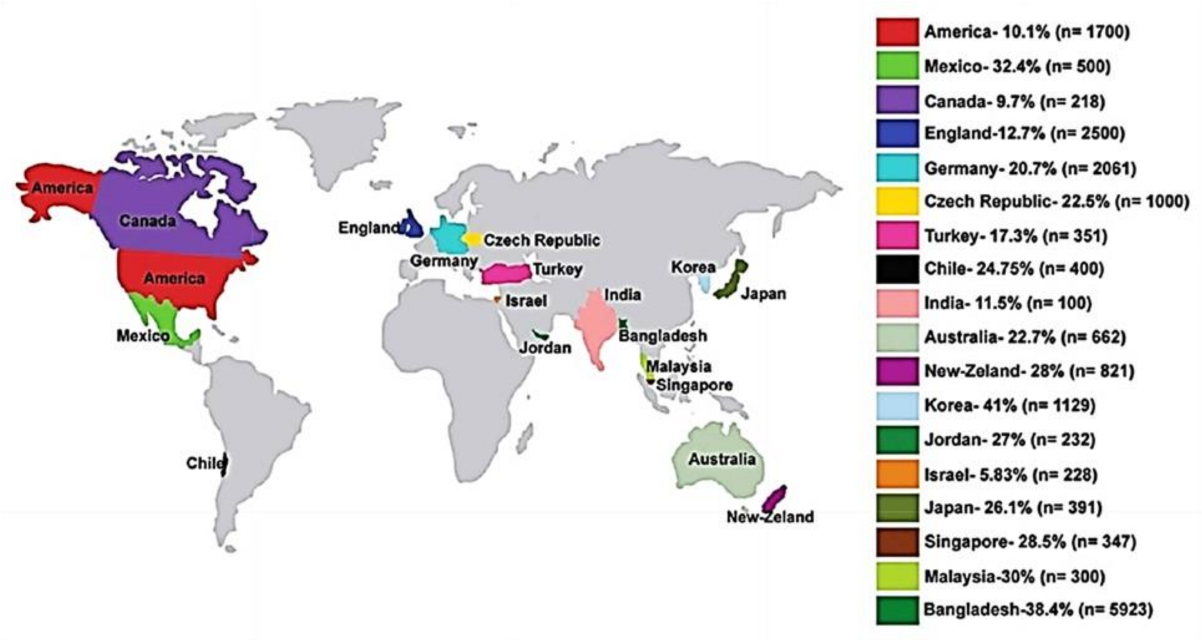

Figure 24: World map showing agenesis rates.[160]

Singh et al. (2017)[161] studied third molar agenesis on DPTs on individuals aged 18-25 and found a 46.7% agenesis of the third molar which is more common in females and in the maxilla than the mandible.[162,163,164]

Although this project looked at lower left third molars, lower right third molars and maxillary third molars may also be used. Sindi et al's study[165] found no statistically significant difference in sex, arch, and side of the mouth or between the right and left third molars, the maxillary and mandibular third molars, and between the males and females when Demirjian and Mooree's[166] classification methods were applied.

The AI method in this study cannot be used where there is a missing lower left third molar. Other teeth may be used, such as left and right mandibular third molars or maxillary molars, however, as previously mentioned, there are problems with the visualisation of maxillary teeth from superimposition. Future development of automated tooth-selection processes by AI may overcome issues of visualisation. Additionally, AI can identify patterns and features of images that are not obvious to human observers.

14.3 Solutions to DAE with missing third molars

To overcome obstacles with missing third molars, the whole DPT or other radiographic image may be useful in future research for implementing AI models rather than an isolated tooth. For example, Otsuki et al. (2023)[167] have used CBCT scans to assess maxillary sinus morphology for sex and age estimation, which can also be seen on a DPT and posteroanterior view radiographs.[168] They found that all the diameters and volumes in both sinuses tended to increase until the mid-20's, and then gradually decreased over time. PA views showing both the frontal and maxillary sinuses can be measured to estimate age and sex.

Therefore, using several radiographic views to train an AI means that the future application can be wider, with applications in identification, sex determination and age estimation and the AI is not limited by a staging system or individual tooth.

15) AI networks and their accuracy

15.1 The design of the network

Pattern recognition is at the heart of all forensic sciences. Neural networks are a set of algorithms inspired by the human brain designed to recognise patterns. They interpret sensory data through labelling or clustering raw input by mathematical modelling. The patterns are numerical, contained in vectors, into which all data (images, sound, text or time series) must be translated.

Five layers of learning for classification were used in this neural network. This was because multiple layers allow the AI to add more depth to the algorithm's processing capabilities: learning to draw shapes around images, separate and classify them.[169] Single-layer neural networks, on the other hand, have just one layer of active units, meaning that inputs connect directly to the outputs.

The quality of predictions by AI largely depends on the labelling and annotation of the training data. For our study, any errors made by the annotators of the images while selecting the lower left third molar or selecting the dentate areas with the bounding boxes could alter the results and give the AI new or irrelevant information (for example, highlighting an area of bone around the roots or missing the cusp of a crown).

During the training phase, the convolutional layers are often alternated with downsizing (also called pooling) layers, which enable the network to learn image features at different scales: initially, low-scale features like corners or points are learned. Then, these features are combined into higher-scale features to manage complex objects in the final layers of the network. If the network is developed to perform classification or regression tasks, a fully connected network is created.[170]

When reusing radiographs from earlier layers of the network to train the model, Hou et al. (2021) found that this introduced non-characteristic areas and extra noise in the image rather than increasing the accuracy.[171] The model was trained to have an accuracy surpassing legal medical expert-level performance. They included individuals aged 1-93 years old and estimated age using deep neural network models. The model calculated the probability of each dental image through a mathematical expectation of the age. A prediction probability was used to estimate the final age estimation. This model used each tooth as a basic unit and extracted key features using different convolutions in each layer of the network.

Although radiographic artificial age estimation is based on prominent characteristics of the teeth, the heat maps of the neural network shows that the teeth were the most important features of the image along with the root area of the tooth (fig 25). They also found that the upper and lower jaw are key areas for identification, which is something that traditional staging methods or atlases don’t take into consideration.

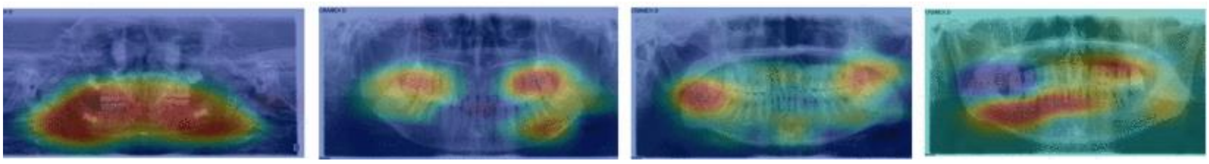

Figure 25: Heat map showing both teeth and jaws as ‘hot spots’.[171]

15.2 How accurate is AI compared to human observers?

Cardoso et al. (2018)[172] assessed the probability of an individual having attained the age of 16 years using dental and skeletal methods and the accuracy of their model was based on its sensitivity and specificity:

- ≥80% gives good prediction
- 50-80% gives reasonable prediction
- <50% gives mediocre prediction

They concluded that legally, it is important for a subject to be judged as accurately as possible to confirm if they are of legal age, meaning that methods with high sensitivity and specificity should be used, and errors kept to a minimum.

For the results of this study, an accuracy of 83% for females and 88% for males falls in the category of good prediction, however, a recent study by Saranya et al. (2021)[129] found more accurate results by using human observers using Demirjian's staging method for the age of 16. They found that "F" was the most accurate stage to predict the attainment of age 16 years with a probability of 93.9% for males and 96.6% for females (although some studies have reported lower accuracies using stage F).[173] Solari and Abramovitch made modifications by introducing two extra root stages at "F" and "G" to estimate the age of 16 more accurately.[128] This shows that manual methods can be more accurate than using AI, especially if the staging method is modified depending on the target age.

By using AI, the teeth are not classified manually into stages, but by the calculated weights, and facilitates the classification of many images at any one time. However, the AI training and validation process can be tedious and time-consuming. Current estimation methods rely on manual measurements and human estimations which come with intra or inter-observer discrepancies and subjectivity which influence the results.[174]

15.3 AI application of staging methods to third molars

Some methods include bounding boxes similar to this research. De Tobel et al. (2017) found that although their methods avoided the need for manual or automatic segmentation, a bounding box was still necessary to fix the ROI of the stage allocation software.[6] The automated techniques by De Tobel et al. (2017)nwere based on CNN's which were used to estimate the age of a person by staging lower third molar development on panoramic radiographs. The system gave excellent results which were comparable to trained examiners.[6]

Other studies have not used bounding boxes as the AI could automatically identify the third molars and assign stages. Leite et al. (2021) used AI for tooth detection and segmentation on DPTs.[175] In our study, the lower third molars were annotated manually and, although there was an "automatic annotation" tool, each tooth was checked and could be manually changed to accurately outline the tooth.

It was noted that automation of tooth detection and segmentation (identification and outline of the exact shapes and boundaries) can be the most challenging step in the development of the AI system and should be as accurate as possible to allow visual pattern recognition. They suggested combining the abilities of AI with expert's analyses to revolutionise healthcare and improve the performance of AI to make predictions or classifications. Future research to improve tooth segmentation by the AI means that a raw image can be used and that the AI will be using information from teeth rather than other aspects of the image.

Pintana et al. (2022)[54] performed a similar study using AI to estimate age using DPTs. Their system automatically located the third molar and applied Demirjian's stages. The lower third molar was located with 99% accuracy. The stages of classification results had similar results to this research, with the accuracy of predictions ranging from 68% to 98% and 83% on average. Despite using a small sample, results showed that in more than 90% of the data, the proposed technique could estimate age with a difference with an overall mean absolute error of 1.94 years and median absolute error of 1.72 years.

Banar et al. (2020)[176] proposed a fully automated method that can localise the third molar before classifying its developmental stages. Their study revealed that the proposed method could yield moderate accuracy, although this was not defined.

Another limitation of our study is that the results were binary: either being over or under 16. If this method was used for identification, there is no range or mean absolute error given. The individual being classified as over 16 gives no further information on what age they are likely to be (16 and several months, 18, 19, 20…). This method is more useful where the age being investigated is specifically 16 and the individual is thought to be close to this age.

In summary, detection and analysis of third molars on DPTs tends to have high specificity and positive predictive value but low sensitivity, negative predictive value and accuracy.[177] Results giving an age range or likelihood ratio can be more useful in some cases, rather than a binary conclusion.

15.4 Combining human observer age estimates with AI

A recent study by Bui et al. (2023) created an AI decision making tool to investigate lower third molars to support human expert decision-making on radiographs from France and Uganda.[178] Two deep learning approaches (Mask R-CNN, U-Net) were compared, leading to a two-part tooth segmentation (apical and coronal). This pilot study illustrates the potential of automating lower third molars by combining a deep learning and a mathematical approach, with 95% accuracy in comparison with an expert.

Therefore, the results of this study supports the development of automated decision making in estimating the chronological age and to contribute to the challenging process of assessing whether an individual is a minor[8] (i.e., under or over 18 years of age) in addition to over or under 16.

15.5 AI fully automated DAE

Milošević et al. (2022)[174] proposed a fully automated estimation of chronological age from DPTs, without the staging process. They used a total of 4035 DPTs from individuals aged between 19-90 years to assess the best convolutional neural network model, performing experiments on the AI system to highlight anatomical regions of the dental system contributing to the age estimation which had a median estimation error of 2.95 years.

Unlike most models which have varying degrees of tolerance to dental anomalies and medical conditions in their exclusion criteria, their proposed model was not affected by dental alterations, caries, medical illnesses or missing teeth. This could save time and be applied to a wider data set where the DPTs can be input as unedited images rather than manually or automatically segmenting individual teeth or including bounding boxes. Future studies could include other radiographic views for age estimation through neural networks and computer learning.

Another automated technique was done by Baydoğan, Baybars and Tuncer (2022) using a deep learning approach with 84% accuracy from DPTs classified into 2 groups: age 2-13 years and age 13-21 years.[179] They used 70% of the images to train and 30% to classify the images and to find the most accurate out of 4 different algorithms. This study also had no annotation or editing of the images before training and classification and used the raw images so human intervention was more limited and the AI performed the complex decision making for DAE.

Seep neural networks and machine learning techniques have been implemented to prevent human errors[180] but humans are still needed to train and supervise the performance of the AI. More studies are needed to compare the accuracy of human observers to AI and determine the benefit of using AI.

16) Applying AI

Although online AI programmes are accessible online, trained AI networks are not developed in common computer systems.[181] For this reason, in research, it is important to have reproducible methods with reproducible results and accuracy when implemented with new data and to monitor its performance over time.

The reproducibility of this study could be done using the DenseNet121 software and annotated DPTs but only by those who have access to, and are trained to use this. The medical images would need to come from an authorised medical professional.

16.1 Access to AI

Dental and medical documentation are becoming increasingly digitised backed up with reliable cloud servers, meaning that these records can play a crucial role in the area of FO for identification as well as age estimation. For example, digital records have been used successfully for disaster victim identification in the World Trade Centre disaster[182] and Indian Ocean tsunami disaster.[183] However, electronic medical records are an area of complex cybersecurity.

The increase of computing power means that advancing technologies (5G, cloud storage, AI and IoT technologies) become more accessible to the general public. Systems that are self-training, self-managing and require little to no experience in coding will enable people with no knowledge or expertise to create their own AI applications and utilise them easily (for example, Microsoft Lobe).[184] Online security and understanding the risks of inadequate security controls is important in the context of data protection and adhering to new legislations such as General Data Protection Regulation (GDPR).[185]

16.2 Security issues

Development of AI technology relies on sensitive data to improve outcomes and the circulating of vast amounts of confidential medical information between unregulated companies comes with risks and is surrounded by privacy concerns.

Firstly, spoofing is the illegal access of a system by operating from another user's authentication information (for example, username and password). If data is held in a database, this can be tampered and modified as unauthorised changes are made to data as it flows between two computers over the internet or other open networks.[186]

Secondly, the 'elevation of privilege' involves an unprivileged user with access to a system compromising and destroying the system.[187] This is especially dangerous because the compromised user would become part of the trusted system. Where patient's medical data is concerned, this raises ethical and legal issues such as a risk of breaching patient confidentiality.

Thirdly, information disclosure involves exposing information to individuals who should not have access to it (for example, an intruder accessing or reading data on a database).[188] Therefore, the development of AI technology should facilitate scientists to advance the technology but prevent criminal acts from being committed through AI as it becomes more accessible.

The security implications of AI were recognised by the European Union who published a proposal for a Regulation of the European Parliament and of the Council establishing uniform rules on artificial intelligence (AI Act) and amending certain Union legislation to regulate the use of artificial intelligence in April 2021.[189] This proposal provides recommendations for companies and governments on using AI technologies and suggests regulatory measures based on risk levels (unacceptable risk, high risk, low risk or minimal risk based on a sector-by-sector and case-by-case approach).

AI may be powerful, helpful, and valuable but unethical use of this new technology may be dangerous so medical professionals must work together with regulatory authorities[190] to ensure security, protection and regulated and responsible management of sensitive data.

16.3 Operation and responsibility

One issue with robot personality is legal liability. AI application involves users, developers, managers, algorithms, data and robots' inputs and therefore, there are many areas in which mistakes can be made. Additionally, this project required a statistician to interpret the results and may be required in the analysis and maintenance of systems where AI is used in real cases.

Holding the developers, operators or producers of Systems of AI liable presents with difficulty because of the specific characteristics of AI systems: their ability to make autonomous decisions, independently of the will of their developers, operators or producers, as well as their ability to learn and gain experience.[191]

However, most studies investigating AI for FO have been experimental in nature and the measure of success in real cases is still to be investigated further: the application is far from being integrated into practice. Humans cannot completely explain the complex processes that characterise the way computational methods elaborate and transform inputs into results. Additionally, AI models need to be trained by quality large datasets to achieve effective results. Therefore, AI may assist the FO but should not replace human intervention. Saleem et al. (2023) describes how although there is no formal training in AI in forensic odontology, they can use AI's capabilities for identification and to contribute to more efficient and reliable legal investigations.[192]

AI engineers should understand the application context of any medical data or images being used[193] so that the results can be expressed in a language or metric that is meaningful to both the researcher and to the field of application. Experts in the field can then interpret the results and give recommendations to improve its effectiveness so there is a shared view of the purpose and intended use of the system. AI experts should be aware of the limitations and advantages of the system during training and testing and collaborate and communicate with other professionals.

Most importantly, the integrity and trustworthiness of AI systems is essential to ensure that AI technologies will work for justice in the forensic field. Therefore, although AI models can be trained in accurate problem solving and decision-making, AI does not replace human decision making and Forensic Odontologists will be required for research and for developing AI methods.

16.4 Monitoring AI decision making

Anatomical and dental morphology variations may affect the performance of CNN systems. For example, from Olze et al. (2012) reported that monoradicular teeth are more resistant to destruction and had large pulpal areas compared with incisors.[194]

Anterior teeth on a DPT have superimposition of the vertebrae and the bite-block causes a blurred area spine in the centre of the image.[195] Molar teeth, on the other hand, have a more complicated morphology, with several roots containing one or several root canals.

As the furcation of a tooth is formed, the inter-radicular structure appears as a small additional area in the lower-middle area of the tooth. The furcation is not attached to the crown or main developing tooth structure. From a computer vision perspective, the image may have two independent parts: the crown and the developing furcation of the roots. AI algorithms struggle to accurately select and analyse these areas.

Artificial intelligence learning is a self-exploratory, self-correcting, and ever-developing process where inevitable bias can result from incorrectly inferring correlation from contingently connected aspects of images. For example, a recently trained CNN model was created to identify wolves and dogs from images: the AI would correlate a 'dog' with the surround 'grass' whereas a 'wolf' was more closely related to 'snow', meaning that dog in the snow was classified as a wolf.[196] Although, during training, the developer of the AI will bring their bias, ultimately it is not the engineer or user of the system who makes the decision, but the algorithm of the AI which will override any human values or biases and mistakes and replicate them.

Therefore, regardless of any human intervention, AI has its own bias. In the context of using lower third molars, the information the AI is using to estimate age is limited to information contained in this annotated area, however, when using an unedited DPT, the AI will not be limited and may use other features of the image apart from the teeth.

Therefore, rational regulatory systems will ensure that AI remains on a healthy trajectory and will not replicate or maximise errors made early in the decision-making process. The use of AI is characterised by opacity, complexity, reliance on data, and autonomous behaviour so the regulation is therefore complex.

16.5 Criteria for dental age estimation and artificial intelligence

In summary, any forensic age method must adhere to four criteria:[197]

1. The work must be presented to the scientific community through peer-reviewed publication.
2. It should contain well-defined methods.
3. It should provide a sufficiently accurate result.
4. It should comply with the principles of medical ethics and legal regulations.

In summary, DAE and AI should benefit the individual or population when to cases, and any individual or organisation must adhere to methods that comply with the above criteria.[39]

17) Ethical issues of radiographic dental age estimation

17.1 Radiation

As previously discussed, using radiographs for dental age estimation is controversial. The Interim Age Estimation Science Advisory Committee states in their report on biological evaluation methods to assist in assessing the age of unaccompanied asylum-seeking children:

> "There are strong views on the use of ionising radiation in the age assessment process and the interim committee has listened to and debated these arguments at length. However, the risk is recognised to be small and the benefits of a reliable age assessment are considerable for the ongoing health and wellbeing of the individual while minimising safeguarding risks."[198]

17.2 Reducing dose and justification of using radiographs

Previously taken radiographs could be used where possible. Otherwise, the dose of radiation can be limited by reducing the exposure time, by implementing digital imaging technology and using electronically-controlled timers.[199] Extra oral radiographs are an alternative to intra-oral radiographs and are more comfortable for the patient. Sectional panoramic or extra-oral bitewing radiographs taken using an OPG machine would reduce the radiation dose compared to a full panoramic radiograph in cases where dental radiographs are not readily available.[200]

Radiation exposure will always carry a certain amount of risk, however, the risk should be balanced with the benefit: a single DPT radiograph is used to estimate age of a child where the exposure is only 0.01 mSv, equivalent to only 1½ days of background sunlight exposure.[201]

Despite the low radiation exposure, radiographic methods may still be considered unethical and unlawful due to safety reasons and exposing individuals to radiation for non-medical reasons. However, medical applications for non-medical reasons are used daily: alcohol and drug testing, aesthetic surgeries and medical treatment, during research experiments and medical assistance to improve sports performance.[202]

17.3 Age estimation implications for individuals and communities

There are often discrepancies between the dental age and chronological age, and there is significant variability in dental development not only by chronological age but also by ethnicity and sex.[203] Individuals who are dentally advanced will have an overestimated age estimation, and, conversely, those who are dentally delayed will have an underestimated age estimation.[204] The impact on these individuals and their communities is great as the date of birth and age (both chronological and biological) determine how individuals participate in society and how they are treated in their communities.

For individuals claiming to be under 16 and where there is doubt about that age, there are concerns about the consequences of placing adults into foster care, schools and health settings designed for younger children and so an age assessment would be undertaken.

The differentiation between an asylum seeker being a minor or an adult can have great impact on the asylum seeker due to the regulations for admitting or refusing them to enter the country.[135] Millions of births go unregistered in developing countries, particularly South Asia and sub-Saharan Africa[205] and even when a birth has been registered, the asylum seeker may have either lost the documentation or have no way of obtaining an authenticated copy, especially in circumstances of war and social turmoil.

17.4 Ethical issues

There are many considerations for the ethics of biological age estimation that can be categorised into ethical, medical and legal issues. Ethical considerations are related to consent of the individual: is it valid, given freely, by a capable individual? How do language and cultural barriers affect this process?

17.5 Medical issues

Medical considerations are the invasiveness of the investigation, the methods used to estimate biological age and their reliability. Accurate methods are required due to the influx of young individuals who are applying for international protection in the context of refugee status and asylum, with no valid documents providing proof of identity. Furthermore, third molar development used for dental age estimation is controversial due to its variability and accuracy.[206]

17.6 Legal issues

Legal considerations are whether an individual aged 18 can be considered an adult if they have been through traumatic and severely threatening circumstances and how much weight is put on mental/psychological maturity compared with physical age. Additionally, child trafficking is a global concern with a rise in numbers in war-torn countries. In 2022, 7019 children were identified as trafficked in England and Wales.[207] Where age estimation is concerned, traffickers of children, notably in the sex industry, may claim that children are older than their true age and the victims are forced to support these claims.[135] The Royal College of Paediatrics and Child Health in the UK state in their guidelines the relevance of a child's social history as part of the assessment. They recommend that age assessments should include "narrative accounts, physical assessment of puberty and growth and cognitive, behavioural and emotional assessments" as part of a holistic evaluation.[135] These assessments have been criticised for a lack of clarity on how a judgement is reached and for the assessor's level of experience or training in child development.[208]

In summary, the ethical issue of misclassification of age in asylum seekers, illegal immigrants and victims of trafficking mean that vulnerable individuals fail to receive appropriate care and support without accurate age estimation. This applies both to children estimated to be adults and adults estimated to be children.

18) Implementing DAE in the UK

18.1 Flaws in the UK asylum seeker age estimation process

The Refugee Council[209] and the Greater Manchester Immigration Aid Unit (GMAIU)[210] both published reports in September 2022 which highlighted significant flaws in the current system. Both reports noted the extreme inaccuracy of initial age assessments by border officials: the former stated that

94% of their own referrals were individuals designated ‘certainly adult’ at the border who were subsequently found to be children. This report added that nationwide this was the case for 75% of at least 450 young people referred to local authorities in 2021.

The GMAIU report also criticised the border assessments on the grounds that they were too short and based mainly upon physical appearance. It was also noted that, from January 2022, an individual need only appear ‘significantly over 18 years of age’ to become age-disputed rather than the previous guidance which was to appear over 25.[211]

Asylum seekers to the UK are considered children if they are under the age of 18. The UK Home Office Immigration System Statistics release showed that currently in 2023, there have been 761 asylum applications made by males and females under 18 and 6,766 applications made by individuals aged 18-29. In 2023, there were 1,765 applications from under 18’s and 12,488 made by 18–29-year-olds.[212] In regard to age disputes for these applications, there were a total of 569 asylum seeker age disputes in 2023 and 1114 in 2022. Out of the 569 in 2023, 255 were resolved to be over 18 and 456 resolved to be under 18.[213]

18.2 Adult or minor status impact on society

Our study showed that the accuracy of DAE was more accurate for males and although the focus was on estimation of age 16, there is a potential to apply the methods for AI to estimate over or under 18 using the lower third molar.

The UK Home Office[214] have recently introduced using scientific methods for assessing the age of asylum seekers. The aim of the change was to ensure that asylum seeking adults posing as children were not gaining support they were not entitled to and remove the safeguarding risks of adults being placed in the children’s care system. The Home Secretary Priti Patel stated:

> “The practice of single grown adult men, masquerading as children claiming asylum is an appalling abuse of our system which we will end. By posing as children, these adult men go on

> to access children's services and schools through deception and deceit; putting children and young adults in school and care at risk.
>
> It is a fact that two thirds of age dispute cases have found that the individual claiming to be a child is actually over the age of 18. I have given more resources and support to local councils to ensure that they apply vigorous and robust tests to check the ages of migrants to stop adult men being automatically classified as children."[215]

Additionally, biological evaluation methods to assist in assessing the age of unaccompanied asylum-seeking children addresses the duty to protect children in care and the wider community, particularly in schools, from individuals who claim to be younger than they are and who aim to gain inappropriate access to the care and care leavers system. There is a major safeguarding issue when adults are housed with children as seen with the Ahmad Otak case.[216] There is an equally important safeguarding issue when minors are incorrectly aged as adults and so inappropriately placed in adult facilities where they may be at risk. Therefore, methods used in forensic age assessment should be robust, repeatable and as accurate as possible.

19) Biological methods

Although the British Dental Association sees dental radiographic estimation as unethical, the article written by the Home Office from 2020 gave examples of Finland and Norway who radiographically examine the dental and wrist radiographs which are combined to estimate the age of an asylum seeker; France who use dental, wrist and clavicle radiographs; and Greece who use dental radiographs and reports from social workers and psychological interviews.[217] There is increased accuracy of age estimation with combining dental and skeletal development.

The dental and skeletal methods include:

- Radiography (x-ray) of the third molar (wisdom teeth)

- Radiography (x-ray) of the bones of the hand and wrist
- Magnetic Resonance Imaging (MRI) of the knee bones
- MRI of the clavicle (collar bone)

Development of the third molar is useful for assessing the age of males and females up to around 18 years of age. Development of the hand/wrist or knee can be used to assess the age of females up to around 16 years of age and males up to around 18 years of age.[137] The clavicle has the longest period of growth-related activity in the human body and is of particular value for assessing age of males and females from 15 to 25 years of age. Because of this, making each of these biological assessments as accurate as possible and combining them is a new proposed method by the UK Government.

19.1 Conclusion of an age estimation

Social workers assessing the age claimed by the asylum seeker can give a conclusion as 'possible' rather than answering if an individual is over or under 16 or 18 years old. Using the biological methods, it is possible to compare the likelihood of the age assigned against the likelihood that the claimed age is possible and show which carries stronger support. However, the likelihood ratio method offers a logical and consistent summary of the evidence and permits greater confidence in the assessment of whether the claimed age is possible.

20) Future work

Future work in the area of AI for DAE could produce results in alternative formats of either a percentage or error range rather than a binary format. Percentage matches are currently used for DNA matching probabilities in court and for DAE, accuracy of above 95% would mean that forensic odontologists may start to use AI as an additional age estimation method to traditional methods in cases.

Training the network to identify the third molar and other teeth, depending on the age, may save time long-term and using more images for training and in validation of the network could increase the accuracy (for example, over 10,000 images).

Following automated identification of teeth, heat maps would allow the information utilised by AI to be presented and analysed in a comprehensible way. As AI makes decisions independently, this would mean that monitoring the performance of the network is possible, along with statistical analysis.

A study comparing AI and staging methods by human observers in simulated cases would allow the comparison of each method separately and, more importantly, using both manual and automated methods in a context which better represents reality.

Finally, AI DAE methods on varying populations, especially European, South American and African, is particularly important since there are many ethnicities of individuals who require age estimation, especially those seeking asylum.

Conclusion and research impact

Most social security services, legal proceedings, and ethical judgments require an accurate age determination or confirmation and where a young person who does not have proper personal identification documents, this necessitates a medicolegal resolution.[167] Traditional methods are influenced by human observer bias and discrepancies are inevitable.

AI techniques have shown promising and accurate results in medicine, dentistry and forensic odontology, sometimes with better performance than humans. AI can be prone to errors and require large data sets to train the models to achieve the best performance.[218] Most studies on AI in forensic odontology have been experimental in nature and are not yet developed enough to be implemented in real cases.

This is the first piece of work to investigate DAE by AI on a Brazilian population focused on age 16. This project found similar accuracy to other AI studies using DPTs for DAE and shows the potential for this technology to assist FO's in future cases.

This study highlights several limitations. Firstly, the results should be considered with care as the DPTs were only from a healthy Brazilian population. Secondly, the results can only be replicated using the same DenseNet121 software: the annotation of the radiographs is time consuming and tedious and statisticians were required to interpret the results. Thirdly, the results were given as a binary conclusion with no error range or likelihood ratio.

Regulation in the training and development of AI requires a multidisciplinary team and vast amounts of data. This includes confidential patient information so the use of AI should comply with relevant regulations and guidelines. Finally, more research is required for the use of AI in practice and while most research has been conducted on Asian populations, research is needed from populations worldwide.

Highlights of this study:

- Convolutional neural network technology works through mathematical modelling to process input data to give a desired output.
- This is the first study to estimate the age of 16 in a sample from Brazil.
- DenseNet121 found 88% accuracy for males and 83% accuracy for females which is a similar accuracy to other AI studies for DAE.
- Population, ethnicity and socioeconomic status affect rates of dental development and bring developmental variability to the sample.
- Further improvement of AI models is required if it is to be used in cases, either to complement human observers or to make decisions independently.

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