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Convolutional Neural Network Model for Sex Determination Using Femur Bones

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***Abstract*— Forensic anthropology is the critical discipline that applies physical anthropology in forensic education. One valuable application is the identification of the biological profile. However, in the aftermath of significant disasters, the identification of human skeletons becomes challenging due to their incompleteness and difficulty determining sex. Researchers have explored alternative indicators to address this issue, including using the femur bone as a reliable sex identifier. The development of artificial intelligence has created a new field called deep learning that has excelled in various applications, including sex determination using the femur bone. In this study, we employ the Convolutional Neural Network (CNN) method to identify the sex of human skeleton shards. A CNN model was trained on 91 CT-scan results of femur bones collected from Universiti Teknologi Malaysia, comprising 50 female and 41 male patients. The data pre-processing involves cropping, and the dataset is divided into training and validation subsets with varying percentages (60:4, 70:30, and 80:20). The constructed CNN architecture exhibits exceptional accuracy, achieving 100% accuracy in both training and validation data. Moreover, the precision, recall, and F1 score attained a perfect score of 1, validating the model's precise predictions. The results of this research demonstrate excellent accuracy, confirming the reliability of the developed model for sex determination. These findings demonstrate that using deep learning for sex determination is a novel and promising approach. The high accuracy of the CNN model provides a valuable tool for sex determination in challenging scenarios. This could have important implications for forensic investigations and help identify victims of disasters and other crimes.**

***Keywords*— CNN; femur; forensic; sex determination.**

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I. Introduction

Forensic anthropology is a field of study that applies scientific knowledge from physical anthropology and often archaeology to collecting and analyzing forensic evidence [1]. Forensic anthropology utilizes principles and techniques from physical anthropology to analyze human remains in the context of legal investigations and forensic education[2]. One of the implementations of forensic anthropology that is often used is the implementation of finding the biological profile of the shards of human's skeleton [3], [4]. And the determination of sex is the first step in deciding the biological profile of a human[5].

Traditionally, anthropologists have used various methods to infer the sex of human bones. These methods include examining the size and shape of the pelvis and skull and skeletal features [6]–[9]. Elvis bone is often used to determine sex [10]–[15]. The pelvis is wider and shallower in females than males, and the skull is typically larger and more robust in males than females. However, in occasions such as great disasters, many shards of human's skeleton are incompletely damaged or degraded, making the sex hard to identify[16]. One of the alternative indicators to identify the sex of a human is by using their spine [13].

The Femur bone is one of the spines inside a human's skeleton. The Femur bone is one of the strongest, robust, resistant bones [11], [17], thus making it often used to determine the sex of a body [18]. Aside from it, the femur bone is also chosen due to its biomechanical relationship with the pelvis bone as the most sexual bone in human's skeleton [11]. Some dimensions of the thighbone, including the diameter and length of the femoral head, including the bicondylar width, have been used to identify the sex of an unknown skeleton individual [19]. The angle of the femur concerning the pelvis is more remarkable in females and straighter in males. The male femur is also thicker and longer than the female femur bones, and this is used as a reference and differentiator between women and men.

Traditional methods of sex determination using femur bones can be time-consuming and inaccurate [20]. These methods typically involve measuring the bone's size and shape and then comparing these measurements to a reference dataset of male and female femur bones. However, this process can be subjective and error-prone, and the accuracy of the results can vary depending on the anthropologist's skill.

As a result, there is a growing interest in Deep Learning to develop more accurate methods of sex determination using femur bones. Deep learning is a subfield of machine learning that makes problem-solving easier because it automates the feature extraction step in the workflow [21]. Deep learning is constructed from some layers of connecting neurons, where each neuron analyzes separated parts of a picture, which are then combined to create a probability where the picture is inserted into an assigned category [22]. Deep learning (DL) has excelled in a variety of applications [23]–[26] and activities related to medical imaging [10], [27]–[31]. Convolutional neural networks (CNNs), in particular, can extract individual features and clinical information from medical photos[32], [33]. Some of the research that discusses the identification of sex using deep learning – such as talked by Bewes et al. [12] – identifies the sex from the shards of human's skeleton using a deep convolutional neural network. The data consists of 900 pictures of skulls from CT-Scan result and showed 95% of accuracy when tested by model. Research conducted by Hassan et al [22] in using CNN architecture to predict the gender and age of individuals using 3D retinal OCT scans. CNN proved to be accurate in predicting the age and sex of individuals. Using the BagNet architecture yields an accurate prediction of age (MAE = 4.0 years with R2 = 0.77) and an acceptable performance for sex determination (AUC = 0.86). Overall, traditional methods of sex determination using femur bones can be time-consuming and inaccurate. Deep learning, especially CNN, offers a promising alternative for developing more accurate and reliable methods of sex determination.

This research uses the CNN method to identify the sex of the shards of human's skeleton. The data used is the result of the CT scan of the femur bone. The dataset is divided into training data and validation data with different percentages. The percentage of the dataset used is 60:4, 70:30, and 80:20. This method is used due to the advantages of CNN when extracting features from picture input, thus increasing the accuracy [10].

II. Material and Method

Creating a CNN model to identify femoral gender requires appropriate steps to create an optimal model. These steps are shown in Fig 1. Fig 1 presents a research framework for classifying gender using the femur bone. The first step involves collecting image data from patients' CT scan results of the femur bone. These data are then divided into training and testing data sets with varying percentages. The collected data is further processed to obtain improved data through cropping and resizing. Once the data has been successfully processed, the training continues, where feature extraction is performed by a Convolutional Neural Network (CNN) as the feature extractor and sigmoid as the classifier for binary classification. Subsequently, the model generated during the training process is evaluated using a confusion matrix.

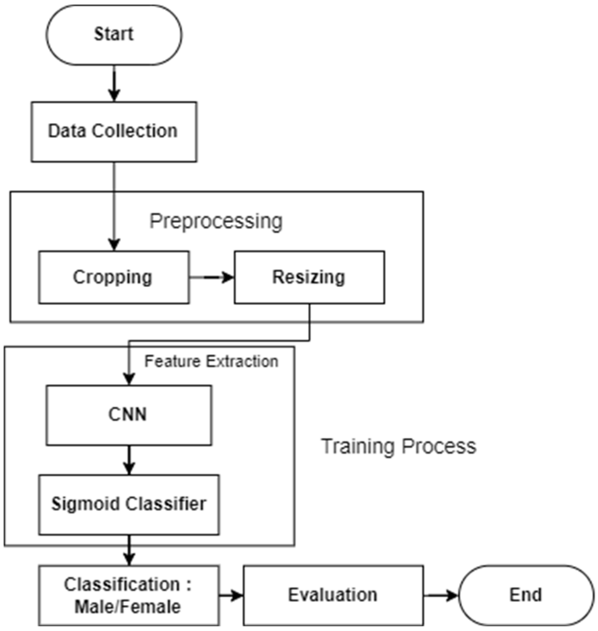

Fig. 1 Research Framework

A. Dataset Collection

The data used in this research results from CT scans of patients from the stomach to the lower abdomen with high accuracy. Fig. 2 shows the data collected in DICOM format, a standard data-saving format for patients' medical records. The data was collected from Universiti Teknologi Malaysia and has not been used in any previous research. There are 91 CT-Scan results, including 50 female patients and 41 male patients. The dataset that is being collected is divided into two, which are training data and validation data. In this research, the data will be divided into a few scenarios. The first scenario is to divide the data into a percentage of 60% training data and 40% validation data. The second divides it into 70% training and 30% evaluation data. Meanwhile, the third scenario divides it into 80% and 20% percentages.


Fig. 2 Result of CT-Scan

B. Pre-Processing Data

The results of the CT scan that have been collected will be entered into the pre-processing data to increase the data quality used, hence supporting the training process. Pre-processing data will be conducted through cropping data. Cropping is used to limit unnecessary data throughout the training process. This research uses the femur as the determining indicator of sex. Cropping data has no exact size requirement as long as the highlighted area covers the femur bone. The cropping process is essential for it to focus on the femur bone. Fig 3. shows the result of the cropping that has been done.

Fig. 3 Result after cropping

C. Architecture of CNN

CNN is one of the neural networks often used in recognizing a pattern, processing a picture, classifying, and many more. CNN is also often applied in face and object recognition and is more reliable than humans' ability to detect an object [34], [35]. CNN uses supervised learning in the implementation and labeled data as a reference to study the connection between the label and the data.

A CNN needs three layers as its main components: the convolutional layer, pooling layer, and fully connected layer. CNN is built by piling some layers as its main components [36]. The convolutional layer is the main layer of the structure of CNN [37], [38]. The convolutional layer creates a new picture called feature maps. The convolutional layer has a filter that is called a convolutional filter. Multiplying the dots between the input data and the filter will create feature maps [39].

The pooling layer plays an important part in the dimension reduction on CNN [28]. Two kinds of pooling layers are commonly used: max-pooling and average pooling. In this research, the pooling layer used is max pooling with a 2×2 kernel size. A Fully connected layer will connect all the neurons from the previous layer to the neurons of the next layer. The fully connected layer represents the feature from the data input into the vector, where this vector will own the vital information of the input [37]. The dropout layer is also used in this research to avoid over-fitting. The dropout layer will only be used in the training phase, where the neurons are chosen randomly and disregarded during the training phase according to the dropout rate [40].

Fig.4 is the illustration of the CNN network architecture that is being used in this research. The implemented CNN architecture consists of a few convolution and pooling layers followed by a fully connected layer. Four convolution layer layers are used (C1, C2, C3, and C4) with 3×3 convolution filter used. The pooling layer is also in four layers (P1, P2, P3, and P4) with a 2×2 pooling window. The input data is a picture of which dimension will be defined and the channel numbers. In this research, the input shape used is 160×160×3, with the 3 standing for RGB (Red Green Blue). The first convolution layer will be inputted with the size 160×160 in convolution with 16 layers.

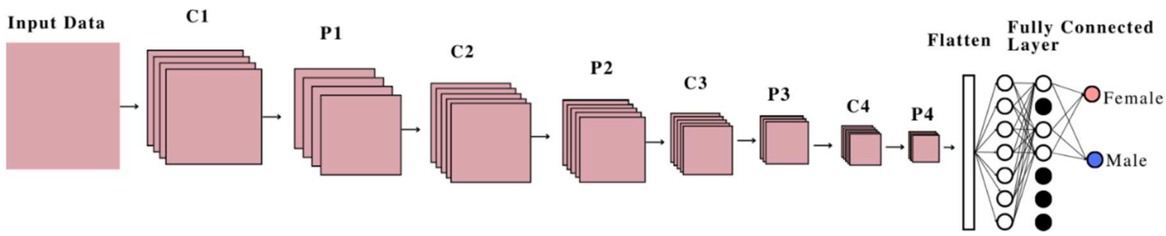

Fig. 4 Network Architecture

The convolution layer used will use ReLU (Rectified Linear Unit) as the activation function. ReLU is a function to increase the non-linearity from a picture, increasing the training process speed and the created model performance [38], [40]. $f(x) = \max(0, x)$ is the equation of ReLU activation function. The second convolution layer is the feature maps created by the previous layer in convolution with 32 filters. The third and fourth convolution layers are doing convolution with four filters. Then, a dense layer with 512 nodes with ReLu as the activation function is used. The dropout layer is being implemented with a 50% dropout rate. The last layer used is the dense layer with a sigmoid activation function. The sigmoid activation function is used as the standard activation in binary classification.

D. Training

In the training process, hyper-parameter is the parameter needed to increase the model's ability to study the data. Hyperparameters significantly influence the performance and convergence of a deep learning model. The difference in using hyper-parameters will create different results in the training process. Selecting appropriate values for hyperparameters is crucial for achieving the desired results. One of the affecting hyper-parameters is the optimizer. The optimization used in this research is RMSprop (Root Squared Propagation), which uses a learning rate of 0.001.

A high learning rate may cause the model to converge quickly but risk overshooting the optimal solution, while a low learning rate may result in slow convergence or getting stuck in suboptimal solutions. Similarly, the choice of optimizer, such as RMSprop, affects how the model updates its parameters, influencing convergence speed and stability. A binary cross-entropy loss was implemented for the sex determination. The training process is conducted in 10 epochs. The learning rate, which determines how rapidly the model is updated and how much the weights are altered during each training epoch, is arguably the most important hyperparameter in deep learning. The number of photos to be fed into the model at each step is determined by the hyperparameter known as batch size. It is important to note that the batch size hyperparameter, which determines the number of training samples processed before updating the model's weights, can affect the convergence speed and the stability of the training process. Therefore, selecting an appropriate batch size is crucial for achieving reliable and accurate model evaluation results.

E. Testing

After the training process is complete, an evaluation will be carried out to measure the success of the resulting model in recognizing the data. Model evaluation is done by testing the model that predicts the test data. The test results are implemented in a confusion matrix. The confusion matrix is one of the most classic decision measures in supervised machine learning. It visualizes the degree of algorithmic confusion within various classes and is independent of the concrete classification algorithm. Confusion Matrix is a visual scoring tool used in machine learning. It will provide valuable insights into the model's predictive capabilities. Using a confusion matrix, some aspects such as accuracy, recall, precision, and F1-Score can be identified through these equations.

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$precision = \frac{TP}{TP+FP} \quad (2)$$

$$recall = \frac{TP}{TP+FN} \quad (3)$$

$$f1-score = \frac{2\times(precison\times recall)}{(precision+recall)} \quad (4)$$

Where:
TP: the amount of positive data and is predicted as positive.
TN: the amount of negative data and is predicted as negative.
FP: the amount of negative data and is predicted as positive.
FN: the amount of positive data and is predicted as negative.

III. Results and Discussion

From the training conducted using CNN architecture with RMSprop optimizer, loss function binary cross-entropy continued using epoch ten times. The training was conducted with four different scenarios. In the first scenario, the data is divided into 60% percentage of training data and 40% evaluation data. The results of the accuracy and loss are illustrated in Fig.5 and Fig.6, respectively.

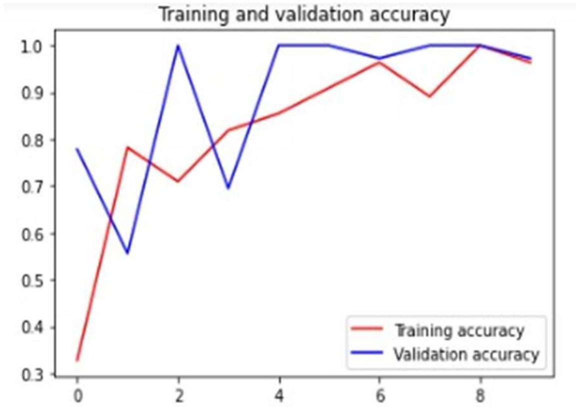

Fig. 5 Accuracy level from training data and the validation of each epoch in scenario 1

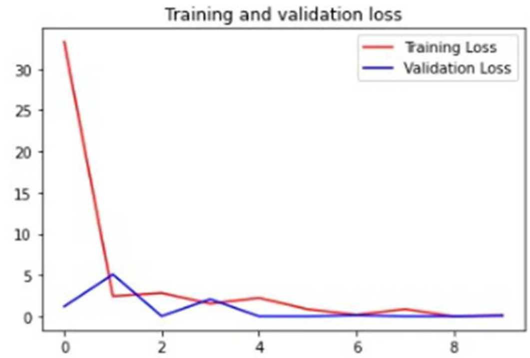

Fig. 6 Loss level from training data and the validation in each epoch on scenario 1

Fig. 5 shows the over-fitting that happened during the training process. This results from insufficient training data, making the model recognize the trained data more than the evaluated data. The final accuracy received during the training in the first scenario is 97%. Fig. 6 shows a similar loss between training and validation. In the second scenario, 70% of the training data and 30% of the evaluation data resulted in the accuracy and loss level illustrated in Fig. 7 and Fig. 8, respectively.

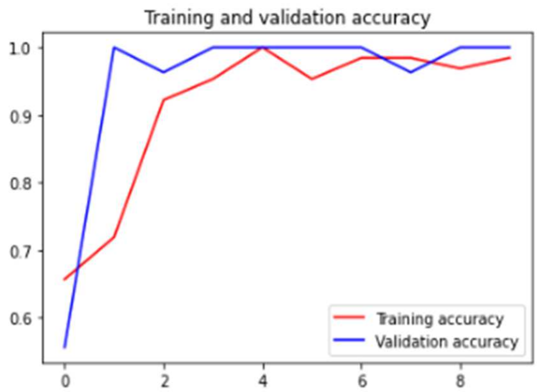

Fig. 7 Accuracy level from training data and the validation of each epoch in scenario 2

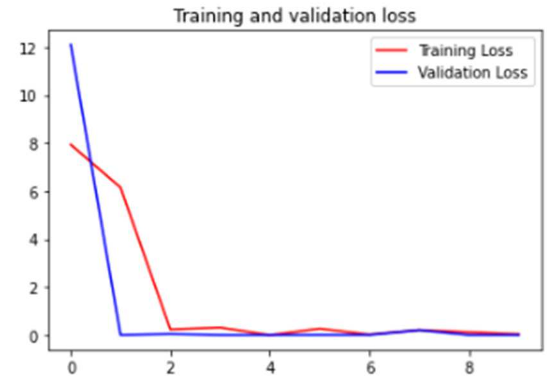

Fig. 8 Loss level from training data and the validation in each epoch on scenario 2

Fig. 7 shows that the training in the second scenario has a more stable result compared to the first scenario. The accuracy resulted during the training process almost reached 100%. As for the third scenario, with 80% of training and 20% of evaluation data, the accuracy and loss levels are shown in Fig. 9 and Fig. 10.

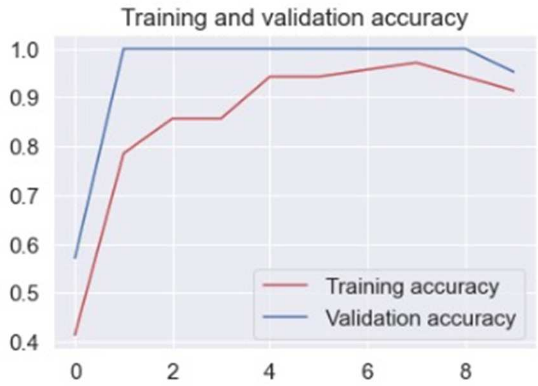

Fig. 9 Accuracy level from training data and the validation of each epoch in scenario 3

Fig. 10 Loss level from training data and the validation in each epoch on scenario 3

Fig. 9 shows the stable graphic of training; however, it is shown that the final accuracy is not as high as the second scenario. The training in the third scenario reached an accuracy of 95%. For the fourth scenario, we are using 90% of the training data and 10% of the validation data. The accuracy and loss level are shown in Fig 11 and 12.

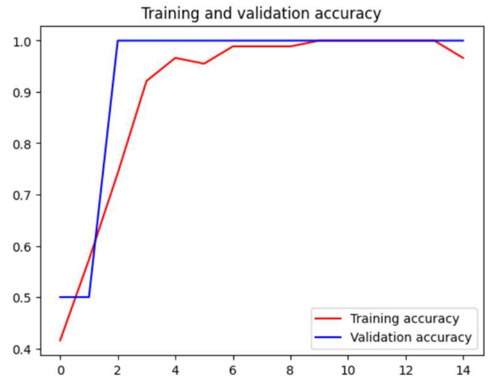

Fig. 11 Accuracy level from training data and the validation of each epoch in scenario 4

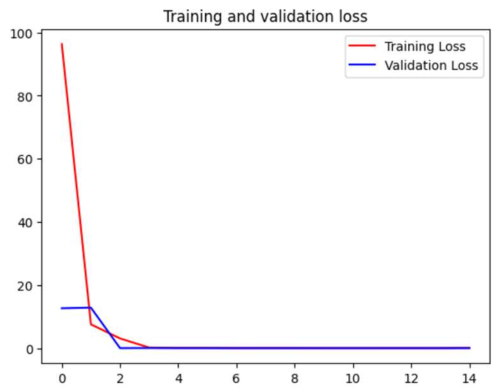

Fig. 12 Loss level from training data and the validation in each epoch on scenario 4

Fig. 11 shows that training in the fourth scenario achieves an accuracy of 95%; however, it is shown that the final accuracy is not as high as the second scenario. The training in the fourth scenario reached an accuracy of 95%. For the fourth scenario, we are using 90% of the training data and 10% validation data. The accuracy and loss level are shown in Fig 11 and 12.

After the training was implemented on the four scenarios, each scenario showed a different result. The second scenario shows the best accuracy among the four. Thus, the model created by the second scenario will be used in identifying sex. Fig. 13 shows the confusion matrix result of predicting 27 data, and the predictions are 100% correct. The sex prediction result uses the CNN model that was created. The accuracy of the result in predicting the male and female and complete prediction can be seen in Fig. 14.

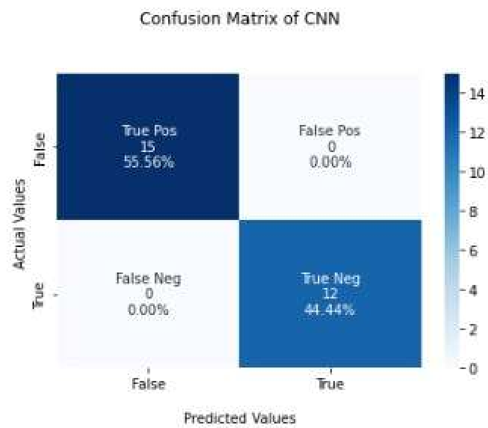

Fig. 13 Confusion matrix on the test of validation data through 27 data

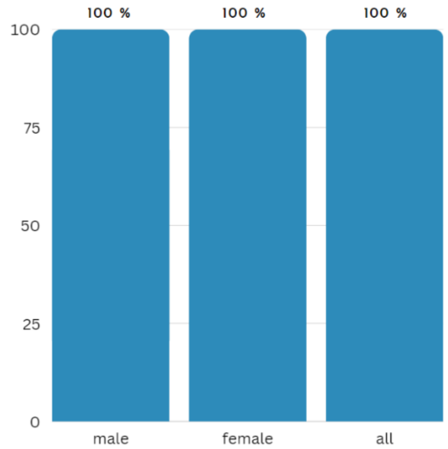

Fig. 14 Precision from the prediction result of male and female.

IV. Conclusion

The architecture of convolutional neural networks (CNNs) is versatile and conceptually simple, making it a powerful tool for various applications. The result of testing this architecture in determining the sex in CT-Scan data is getting a perfectly exact result. This architecture can be trained to assume an individual's sex using a CT-Scan from the stomach to the lower with high accuracy. This method can be used easily without expertise, is quick-used, and can potentially remove the bias of estimating sex from shards of a skeleton, such as using femur bone. This architecture can potentially democratize forensic anthropology and affect archeology and forensic studies.

The only input used in the artificial neuron in this research is the CT-scan picture of a patient's bone in the femur bone part from the front perspective. Without previous instruction or knowledge about dimorphic sex anatomy, CNN is useful for predicting sex. When the model is being tested in a CT-Scan validation dataset that has never been tested and comes from the same data population, the result shows a good accuracy in determining the sex. This suggests that the learned features and patterns generalize effectively to new, unseen data samples, reinforcing the robustness and reliability of the trained CNN model.

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