International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8074
Article Received: 18 June 2023 Revised: 12 August 2023 Accepted: 01 September 2023

A Real Time Employee Attendance Monitoring System using ANN

Jaishree Jain[1], Jatin Chauhan[2], Anushka Sharma[3], Shashank Sahu[4], Ankita Rani[5]
Department of Computer Science & Engineering, Ajay Kumar Garg Engineering College, Ghaziabad-201009, India
[1]Jaishree3112@gmail.com, [2]chauhanjatin1608@gmail.com,[3]Anushkasharma180202@gmail.com, [4]sahushashank75@gmail.com
[5]ankita.apex7@gmail.com

Abstract: Face recognition refers to the technology that examines and contrasts a person's face characteristics to recognise or verify their identity. Recently, this technology has drawn a lot of attention due to the potential uses it may have in security, marketing, and law enforcement. Face recognition involves studying a picture or video of a person's face to identify features like the space between their eyes, the contour of their nose, and the curve of their mouth. The person's identity is then established or verified by comparing these characteristics to a database of previously saved pictures. A series of techniques called facial recognition algorithms are used to identify and authenticate persons based on the features of their faces. These algorithms compare a person's facial attributes to those in a database of recognised faces by looking at things like the shape of their face, the distance between their eyes, and other distinctive facial features. There are many different types of face recognition algorithms, including geometric-based algorithms, appearance-based algorithms, and hybrid algorithms that combine both approaches. Geometric-based algorithms employ the geometry of face traits to identify and validate people, while appearance-based algorithms use image processing techniques to compare the patterns and textures of facial features. Recent advances in deep learning have significantly improved the accuracy of facial recognition algorithms. Artificial Neural Network (ANN) has shown to be highly effective and have been used in a range of applications, including mobile devices, security, and surveillance. Face recognition algorithms provide advantages, but there are also moral dilemmas with regard to its application, such as potential biases and privacy difficulties. As technology advances, it is imperative to address these problems and ensure that face recognition algorithms are used ethically and responsibly.

Keywords: Neural Network, Face detection, Artificial Neural Networks, Deep Neural Networks.

I. Introduction

Face recognition technology is essential in today's digital world and is used in every industry practically. By using a facial recognition system, it is possible to recognise or confirm a person from a digital image. To evaluate a classroom, accurate attendance data are essential. However, manual attendance recording may lead to mistakes, missing classes, or several entries. These flaws might be fixed with the use of the Face Recognition-based attendance system. In the suggested model, the system is trained using the authorized students (A Krenker et al., 2011). Additionally, the facial recognition technology can be utilized in businesses, schools, colleges, and other places to track attendance (Er. P Kumar and Er.P Sharma, 2014). Furthermore, there's a potential that a proxy will show up. Consequently, the demand for this system rises. The technology is based on the ability to identify or verify a person's identity by looking at their facial features (N Jindal and V Kumar,2013). This review article will examine the most current advancements in deep learning, computer vision, and other fields to provide insights into the challenges and probable future directions of face recognition technology.

Face detection is the process of finding faces in photos or videos by teaching a computer algorithm to identify the distinctive features of a human face, such as the eyes, nose, mouth, and other facial features (S SudhakarFarfade et al., 2015). A sizable dataset of labeled images can be used to train the algorithm, with the non-face regions being labeled as negative samples and the faces being annotated and marked as positive samples. The steps involved in face detection are as in Fig.1:

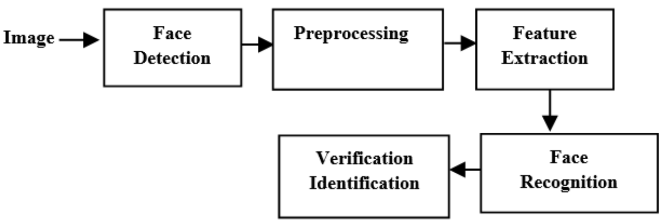

Fig. 1. Architecture of face Recognition system

The four essential parts of every biometric system are shown in Fig. 1: face detection, pre-processing, feature extraction, and face recognition. As depicted in Fig. 1, the first task of the face recognition system is to take a photo using a camera, a video camera, or a database. This photo is then passed on to the next phase, which is covered in this section.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8074
***Article Received:** 18 June 2023 **Revised:** 12 August 2023 **Accepted:** 01 September 2023*

1.1 Face Detection

A multitude of computer applications employ the face detection approach to locate people's faces in digital photos. The psychological mechanism through which people find and focus on faces in a visual context is known as face detection (Bishop and C. M.,1995).

1.2. Pre-processing

Pre-processing methods can be used in this stage to eliminate undesired noise, blur, shifting lighting conditions, and shadowing effects. This step serves as the pre-processing for face identification. The feature extraction procedure will be employed once we obtain a fine, smooth facial picture (LeCun, Y et al., 2015)

1.3. Feature Extraction

The features of the face can now be extracted using a feature extraction technique. Extractions are used in information packing, dimension reduction, salience extraction, and noise cleansing. A face patch is frequently converted into a vector with predetermined dimensions or a collection of fiduciary points and their related coordinates after completing this phase (Lin, T. Y et al., 2015)

1.4 Face recognition

Algorithms are used in facial recognition to identify or confirm a person's identification based on visual traits as in Fig.2. Biometric identification is used. It entails taking pictures or videos of someone's face and assessing a variety of features, including the separation between their eyes, the contour of their nose, and the curvature of their lips. Potential uses for this technology in security systems, police enforcement, and marketing (Andrew G. Howard et al., 2017)

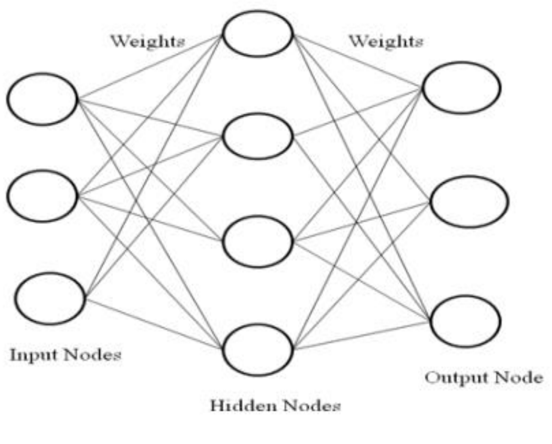

Fig. 2. Artificial Neural Network

Natural language processing, image and audio identification, anomaly detection, and other processes may all be done using neural networks. They are a common tool in the artificial intelligence community and have demonstrated cutting-edge performance in several applications (Kenneth O. Stanley andRistoMiikkulainen, 2002).

II. TOPOLOGIES OF NEURAL NETWORK

There are several common topologies, or architectures, of neural networks. Here are some examples:

2.1. Feed forward Neural Networks (FNNs)

The simplest kind of neural network is this one. Without any loops or feedback, the information moves directly from the input layer to the output layer as in Fig.3. (Zhenan Sun et al., 2014)

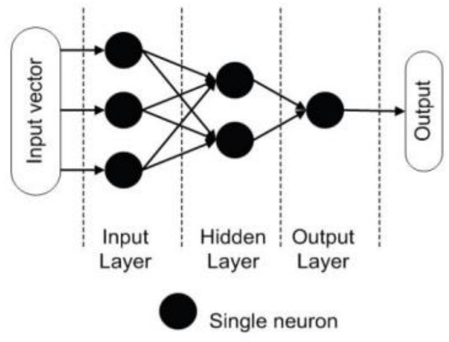

Fig. 3. Feed-forward (FNN)

2.2. Recurrent Neural Networks (RNNs)

In an RNN, the information can flow in both directions, and there can be loops or feedback. RNNs are therefore helpful for processing data sequences like time series or phrases in natural language for eg Fig.4. (https://www.researchgate.net/publication/326261079).

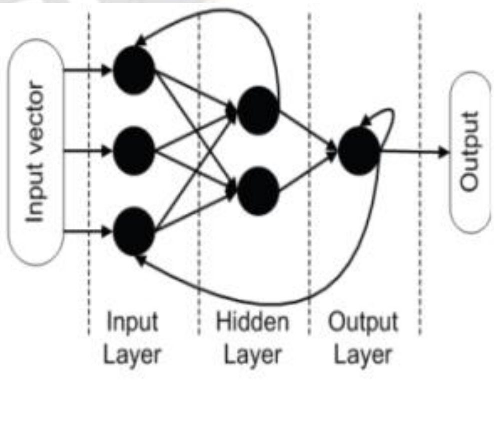

Fig. 4. Recurrent Neural Networks (RNNs) Topology of an Artificial Neural Network

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8074
***Article Received:** 18 June 2023 **Revised:** 12 August 2023 **Accepted:** 01 September 2023*

2.3. Convolution Neural Networks (CNNs)

For image recognition applications, CNNs are often utilised. They employ pooling layers to make the feature maps less dimensional and convolution layers to extract features from the input picture as in Fig.5.

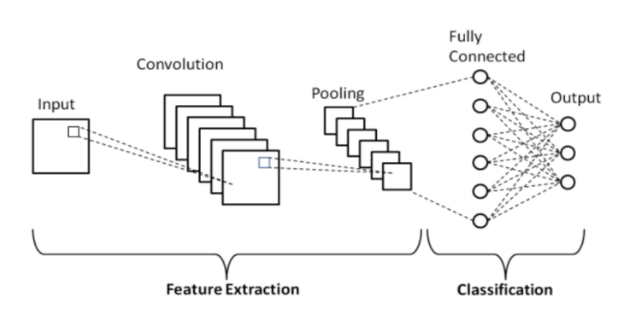

Fig. 5. Convolution Neural Networks (CNNs)

2.4. Auto encoders

An artificial neural network called an auto encoder can learn to compress and reconstruct data by representing it in a lower-dimensional way. They can be used for tasks like dimensionality reduction, data denoising, and the creation of new data because they have two parts: an encoder and a decoder as shown in Fig.6 (Hapani, Smit,et al. 2018).

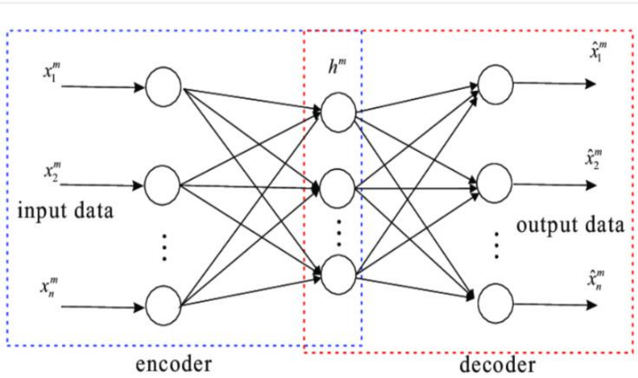

Fig. 6. Auto encoders

2. 5. Varieties of synthetic neural networks

The neural network architecture of an input layer, an output layer, and a single layer of hidden neurons (see section 2.5.1). Neurons in the hidden layer send signals to those in the output layer and receive input from the input layer to exchange information. Examples of applications for this architecture include regression and classification issues Fig. 7 (Akbar, Md Sajid, et al., 2018).

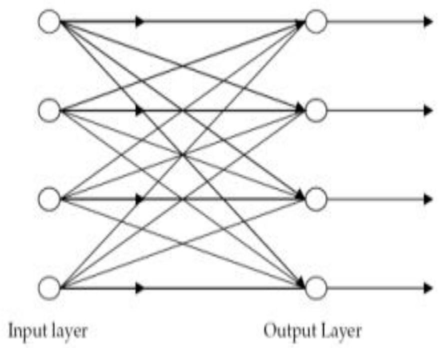

Fig. 7. Single Layer Feed Forward Network

2.5.1. Multilayer Feed Forward Network

The input and output layers of a multilayer feedforward network, a type of neural network architecture, are separated by multiple layers of hidden neurons as in Fig. 8. For challenging tasks like speech and image recognition, it is commonly used.(Okokpujie, Kennedy O., et al., 2017)

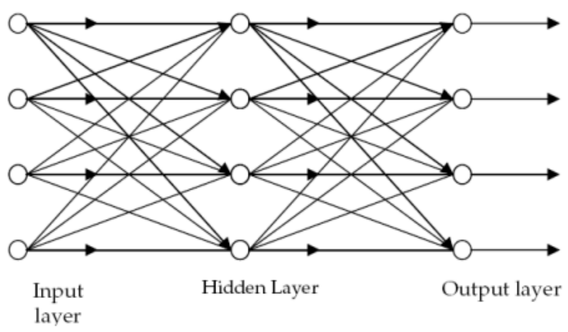

Fig. 8. Multilayer Feed Forward Network

2.5.2. Recurrent Network

The ability to handle sequential input, such as time series or plain English, is provided by an RNN, a type of neural network design that allows feedback connections as in Fig.9 (Rathod, Hemantkumar, et al., 2017).

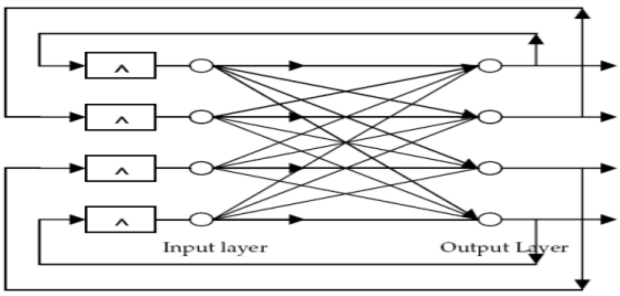

Fig. 9. Recurrent Connected Network

III. ARTIFICIAL NEURAL NETWORKS APPROACHES FOR FACE DETECTION

Artificial neural networks (ANNs) have been widely applied to face detection difficulties. Methods including convolutional neural networks (CNNs), deep belief networks (DBNs), and recursive neural networks (RNNs) have demonstrated significant potential for accurately identifying faces in pictures and videos with a variety of applications in security, surveillance, and marketing (Siswanto et al., 2014).

3.1. PCA with Artificial Neural Networks

The Principal Component Analysis (PCA) dimensionality reduction approach is utilised for huge datasets. The original high-dimensional data is scaled down while keeping as much volatility as is practical. PCA plays a part in image processing, where it is commonly used in applications like face identification.

Artificial neural networks (ANNs) have also been extensively used in the detection and recognition of faces. A situation known as the "curse of dimensionality" refers to the tendency of an artificial neural network (ANN) to perform worse as the complexity of its inputs increases. To get around this issue, PCA is widely used as a pre-processing step before ANNs in facial recognition applications. PCA creates a set of low-dimensional features from the high-dimensional input data, which are subsequently fed into the ANN (Lukas, Samuel, et al., 2016).

3.2. Deep Convolution Neural Networks

Deep convolution neural networks (CNNs) (S SudhakarFarfade et al., 2015) are a type of neural network used for image and video processing. With regard to a variety of computer vision tasks, including as object identification, recognition, and segmentation, these networks have displayed astounding performance. They have also been employed in projects requiring speech recognition and natural language processing. The accuracy of prediction tasks may be increased by creating hierarchical representations of the input data due to the complexity and depth of CNNs. CNN training usually needs a lot of data and computing power, although recent improvements in hardware and software have improved them. (https://becominghuman.ai/face-detection-using-opencv-with-haarcascade-classifiers).

3.3. Radial Basis Function Neural Networks

An RBF neural network is an artificial neural network that uses radial basis functions as activation functions. Applications involving classification and function approximation typically employ RBF networks (Bishop and C. M.,1995). RBF networks have demonstrated promising results in a number of applications, including pattern recognition, time series forecasting, and system identification. They are frequently used for classification and regression problems. The RBF layer can be taught using supervised learning techniques like back propagation or unsupervised learning techniques like K-means clustering. RBF networks use less training data and are easier to install than other types of neural networks, making them suitable for smaller datasets (https://www.superdatascience.com/blogs/opencv-face-recognition).

3.4. Convolution Neural Network Cascade

A deep learning architecture called Convolution Neural Network Cascade (CNN-Cascade) is made up of several convolution neural networks that are connected in a cascade. Each network has been trained to carry out a particular subtask, like object localisation, object detection, or object recognition. Each network's outputs are fed into the following network in the cascade, whose final output yields the overall forecast. The benefit of CNN-Cascade is that it can accomplish difficult jobs with great accuracy while being computationally effective. Additionally, it enables better management of background clutter, size change, and occlusion.On a variety of image identification tasks, including the ImageNet challenge, which involves classifying photos into one of 1,000 categories, CNNs have attained state-of-the-art performance[20].

3.5 Bilinear CNNs

A sort of deep learning architecture known as a bilinear convolution neural network (B-CNN) combines two streams of convolution neural networks. A bilinear feature representation is produced by multiplying the outputs of the two streams element-by-element, which each extracts a separate feature from the input images. The input photos are encoded with both local and global spatial information using this feature representation, improving prediction tasks' accuracy. Tasks requiring visual recognition have gone well for them. They are suited for challenging visual tasks where spatial relationships are crucial since they can also record higher-level interactions between features.

3.6. Back Propagation Network (BPN) And Radial Basis Function Network (RBF)

The back propagation network (BPN) and the radial basis function network (RBF) are two forms of artificial neural networks that are frequently used for supervised learning tasks. The learning algorithm of a multilayer feedforward network known as BPN is backpropagation. The weights of the three layers—input, hidden, and output—are continuously changed to lessen the gap between predicted and

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8074
***Article Received:** 18 June 2023 **Revised:** 12 August 2023 **Accepted:** 01 September 2023*

actual outcomes. Radial basis functions, on the other hand, are used as activation functions in the buried layer by RBF.

3.7. Retinal Connected Neural Network (RCNN)

An artificial neural network called a retinal connected neural network (RCNN) is inspired by the retina of the human eye. Its layers of linked neurons work together to feed forwardly interpret visual data. Traditional convolution neural networks use local receptive fields, whereas RCNN uses global receptive fields, enabling processing of a greater variety of visual inputs. The network can learn to extract features that can adjust to changes in scale, lighting, and orientation. It is designed to recognise objects in images. It has the potential to be used in robotics, autonomous vehicles, and medical imaging.

3.8. Rotation Invariant Neural Network (RINN)

By combining a number of feature maps, each of which captures a distinct rotation angle of the object, it achieves rotation invariance. The network is trained to learn robust qualities that are rotation-invariant using a sequence of images with different orientations. Once trained, the network can accurately classify rotating objects. It has the potential to be used in a wide range of applications, including robotics, surveillance, and autonomous vehicles. RINN has demonstrated promising results in a variety of computer vision tasks, including object detection, digit classification, and character recognition.

3.9. Fast Neural Network

Fast neural networks (FNNs), a type of artificial neural network, are designed for processing large datasets quickly. It mixes parallel processing and distributed memory structures to accelerate training and prediction workloads. The dataset is divided into more manageable subsets that FNN may analyse in parallel. Using communication-efficient methods, FNN synchronises the subsets across many processing units. To speed convergence and reduce overfitting, it also uses efficient regularisation and weight initialization techniques. Real-time systems that require high-speed processing, such autonomous vehicles, robots, and video surveillance, have the potential to use FNN. FNN has shown promising outcomes in a number of applications, such as voice and picture recognition. One example of a rapid architecture is the MobileNet.

3.10. Evolutionary Optimization of Neural Networks

Evolutionary optimisation of neural networks is a type of optimisation technique where the design and parameters of neural networks are trained and optimised using evolutionary algorithms. Particle swarm optimisation, genetic algorithms, and other evolutionary techniques are used to determine the best set of weights, biases, and network structure that minimises the error between predicted and actual outputs. For a range of applications, including as pattern recognition, classification, and regression, evolutionary optimisation can improve the performance of neural networks. The advantage of it is that it can handle high-dimensional optimisation problems and explore a large search space for the best answers. This methodology has the potential to offer better answers than traditional optimisation techniques and is helpful in a variety of situations, including robotics, autonomous vehicles, and natural language processing. One example of this approach is the Neuro Evolution of Augmenting Topologies (NEAT) algorithm.

3.11. Multilayer Perceptron (MLP)

Each perceptron unit uses a nonlinear activation function to produce output after receiving input from the layer below. In supervised learning tasks like classification and regression, MLPs are frequently utilised. Backpropagation is a training method for neural networks that minimises the difference between expected and actual outputs by adjusting the weights and biases of the perceptron units. MLPs are able to approximate any continuous function and can learn intricate nonlinear correlations in the data. They have been successfully used in a number of fields, including speech recognition, computer vision, and natural language process.

3.12.Gabor Wavelet Faces with ANN

Face identification using Gabor wavelet faces and artificial neural networks (ANN) is a computer vision technology. The face's local texture and shape information are captured using gabor wavelets, and the ANN is trained to recognise the features that were extracted. This method has the benefit of being resistant to changes in stance, lighting, and facial expression, and it has demonstrated great accuracy in face recognition tests. It has been used in numerous practical contexts, including surveillance, access control, and computer-human interaction. GCNN attained cutting-edge results on a number of face recognition benchmarks.

3.13 Hybrid Wavelet Neural Network and Switching Particle Swarm Optimization Algorithm

The structure and weights of the WNN are optimised by combining wavelet analysis, artificial neural networks, and particle swarm optimisation. In order to extract features from the data, wavelet analysis is employed. The optimal weights and biases for the WNN are then determined using the particle swarm optimisation method. In a variety of applications, such as flaw identification, image processing, and voice recognition, this technique has yielded positive results. It

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8074
***Article Received:** 18 June 2023 **Revised:** 12 August 2023 **Accepted:** 01 September 2023*

benefits from the ability to manage highly dimensional and nonlinear data, and it can increase the precision of classification tasks.

IV. PROPOSED METHODOLOGY

Systems layout is a process that identifies the requirements for the architecture, components, modules, interfaces, and records. The age of face detection makes it possible to find human faces in virtual images and video frames. The technology for recognising things in digital photos and movies according to their timings. The suggested method uses Haar Cascade, PCA, and ANN to develop an effective Face Detection and Recognition strategy that is independent of differences in variables like colour, hairdo, different face expressions, etc. Fig. 10 depicts the suggested methodology's process flow.

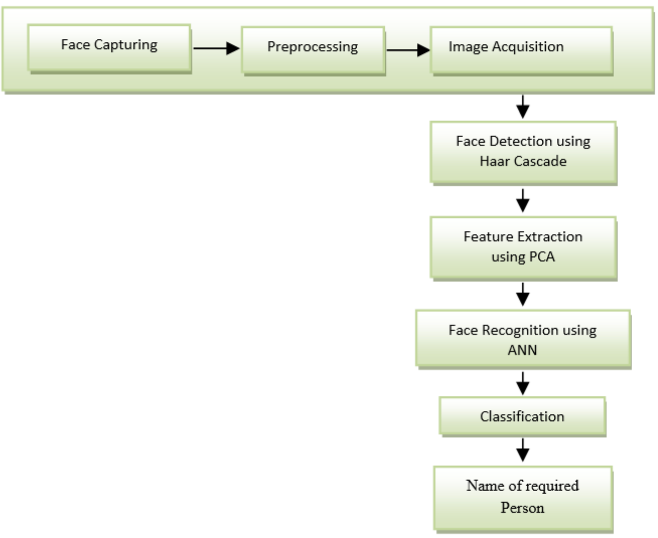

Fig. 10. Flow chart of Proposed Methodology

4.1 Pre-processing

It is suggested to use a common image database that is easily accessible in both colour and grayscale. The acquired image is subjected to contrast stretching during the pre-processing stage, which results in the white pixels becoming whiter and the black pixels.

4.2 Feature Extraction Using Principal Component Analysis (PCA)

The main goals of a significant aspect analysis are to evaluate data in order to spot patterns and to discover methods for reducing the computational complexity of the dataset with the least amount of factual loss. In order to identify human faces, they can extract facial functions with greater precision.

4.3 Face Recognition System by Using PCA with ANN

The main goals of a significant aspect analysis are to evaluate data in order to spot patterns and to discover methods for reducing the computational complexity of the dataset with the least amount of factual loss. In order to identify human faces, they can extract facial functions with greater precision. The activation moves from the input layer to the output layer via connections between each layer. Sweeps of the community, which can be both forward and backward sweeps, make up the back-propagation set of rules.

4.4 Face Detection using Haar Cascade

In order to locate faces in photos, the Haar cascade approach is used. Haar cascade was chosen as a detection method due to its high detection rate and real-time functionality. The detector functions best with frontal facial images and can accommodate a 45° rotation of the face around the vertical and horizontal axes. The three main concepts that let it to function in real time are the integral image, Ada Boost, and cascade structure. An effective method for generating the total pixel intensities in a given image rectangle is the Integral Image algorithm. It is employed to quickly compute Haar-like features. Calculating the sum of a rectangular area within the original image is fairly challenging.

4.5 Post-Processing

In the proposed system, the names are shown in a visual output once the faces of the people are recognised. The finished product is created by the database machine's built-in exporting mechanism. Real-time video might be able to display this created data. This makes sure that those whose faces the gadget can no longer recognise accurately must search the database. Giving them the chance to fix the device and make it more precise and stable.

4.6 Steps involved in face detection process

- Use an external camera or a webcam to take images of people's faces. An HD camera specifically for this purpose.
- Verify the attendance record.
- Track down an unknown person.
- It is always necessary to identify faces in photographs.
- It is necessary to identify the bounding boxes for the face photographs.
- Calculate the overall attendance based on the recognised faces.
- Decreasing the total number of faces discovered.
- Resize the clipped facial images so that they are compatible with the identification scale.
- Faces should be added to the database.
- Recognise the faces that have been stored in the database.
- Recognise each face that Face Detector has cropped out one at a time.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8074
***Article Received:** 18 June 2023 **Revised:** 12 August 2023 **Accepted:** 01 September 2023*

- The name of the output picture should be discernible above the image in the plot area

The interface of the system as shown in Fig. 11 below:

Proposed Algorithm

- **Take a picture of the employee.**
- **Use PCA Algorithm to extract the features**
- **Applying Haar Cascade for face detection**
- **Convert to gray scale , apply histogram equalisation (Pre-processing)**
- **Apply ANN for feature matching**
- **if enrolment**
  then store in database
  else
  apply PCA to extract features
  End
- **Post Processing**

Fig.11.Proposed Algorithm

V. RESULTS & DISCUSSION

The following graph shows the outcomes of the suggested face detection using MATLAB's vision cascade detector, which is based on a different machine learning method. Here, users will primarily have access to three options: teacher registration, student registration, and attendance marking. The students must thoroughly fill out the student registration form. The webcam starts up right away after hitting the register button, and a window resembling the one in Fig. 12 opens and starts to recognise the faces in the frame. It begins taking photographs automatically when 60 samples have been collected or when CRTL+Q is pressed as in Fig. 13. The edited photos will subsequently be placed in the training pictures folder as shown in Fig. 14. The faculties must fill out the provided faculty registration form with their email addresses and the correct course codes as shown in Fig. 15. This is important because a mail list of students who missed class will eventually be sent to the various faculties.

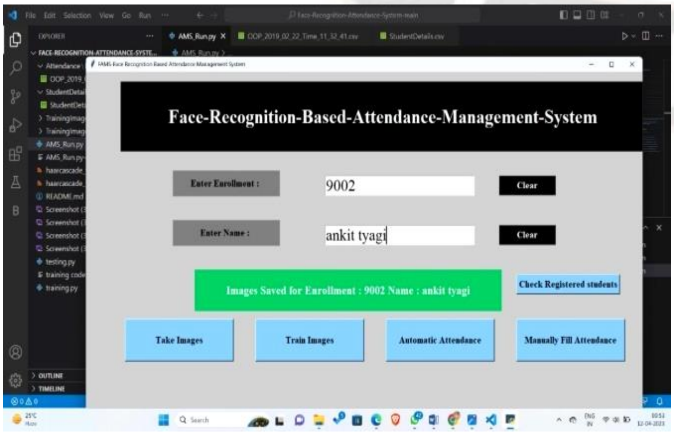

Fig. 12. Student Registration

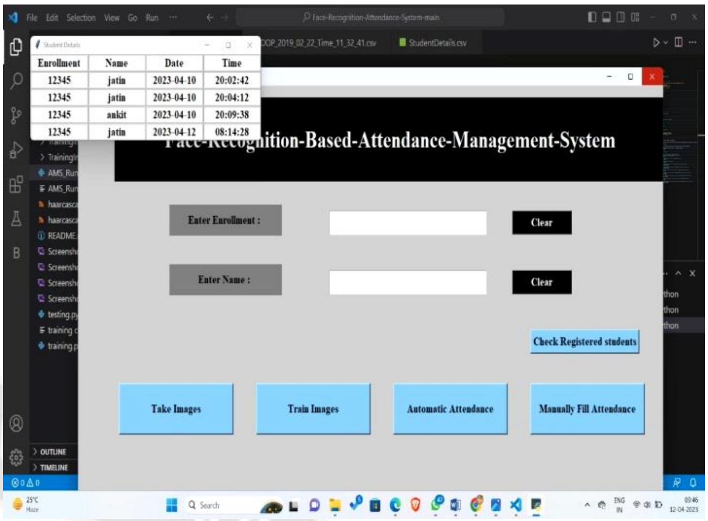

Fig. 13. Enrolment Details

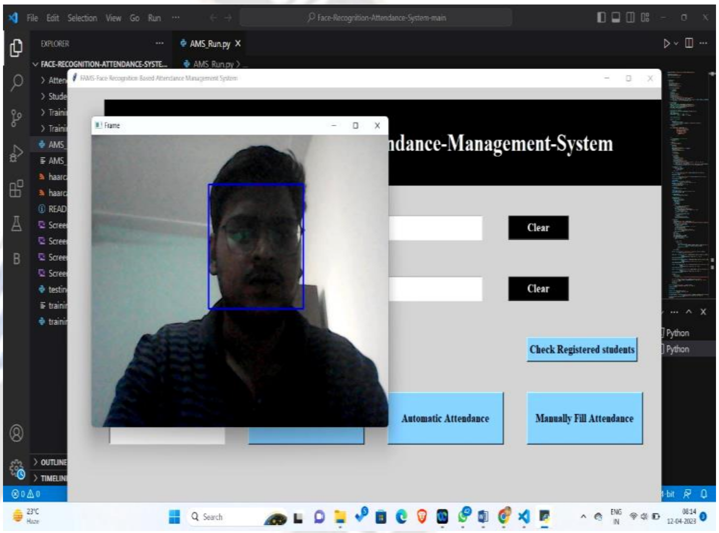

Fig. 14. Face Detection

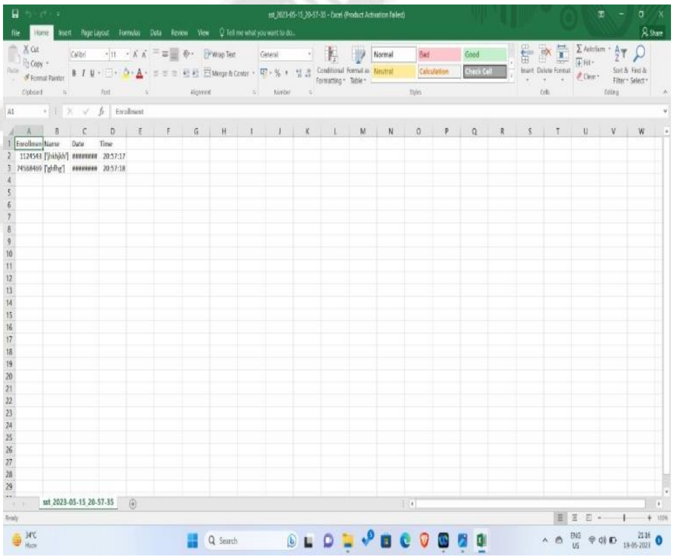

Fig. 15.Attendance Sheet

ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8074
Article Received: 18 June 2023 Revised: 12 August 2023 Accepted: 01 September 2023

Table 1. The accuracy of various ANN approaches has been compared in research using various Databases.

Sr.no	Methodology	Recognition Rate
1	PCA with ANN Face recognition system	95.45%
2	DNN	91.79%
3	RBNNs	97.56%
4	CNN	85.1%
5	B-CNN	95.3%
6	RCNN	90.3%
7	RINN	90.6%
8	MRC&MLP NEURAL Network	91.6%
9	Gabor Wavelet Faces with ANN	93%
10	WNN	89.2%
11	**Proposed Methodology(PCA+ ANN + Haar Cascade)**	98.88%

As shown in Table 1, the suggested method's face recognition and detection accuracy are compared to those of the existing approaches. 72% of images can be recognised using the PCA technique, while 92% can be recognised using the ANN algorithm. 90% accurate face detection and identification using DNN was proposed by S. Sudhakar et al. (S SudhakarFarfade et al., 2015) Face detection and recognition using CNN was suggested by Andrew G et al. (Andrew G. Howard et al., 2017)with an accuracy of 85.1%. Accuracy rates for face detection and recognition using Radial Basis CNN and Bilinear CNN are 90.3% and 95.3%, respectively. With accuracy of 93%, Zhenan Sun et al. (Zhenan Sun et al., 2014) suggested Gabor Wavelet Faces. The suggested approach, which combines ANN, PCA, and Haar Cascade, achieved an image identification rate of 98.88%. Hence, the suggested approach is more accurate in identifying a person in an image in comparison with the other methods as shown in Fig. 16.

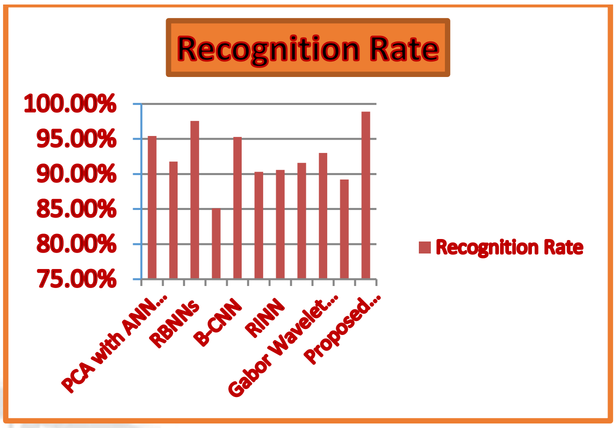

Fig. 16: Recognition Rate

Here, we examine that certain methods are more accurate at recognising faces, but face recognition still has significant limits.

VI. CONCLUSION

In summary, facial recognition algorithms have significantly improved in terms of efficiency and accuracy, but they still have issues with things like lighting, stance, expression, and privacy problems. Deep learning-based algorithms have produced encouraging results and are being utilised more often in a wide range of applications. Face recognition's moral ramifications should be carefully considered. The particular application and the available resources will determine which algorithm is used. Face recognition algorithms have the potential to revolutionise numerous industries, but it is imperative to guarantee that they are used in a responsible, open, and fair manner. To address the remaining issues and create stronger and more dependable algorithms, more research is required. The remaining issues with facial recognition algorithms, such as handling changes in lighting, position, and expression, could be the subject of future research. Research might also examine the moral ramifications of face recognition systems and create rules for proper application. To guarantee that algorithms are trained on a representative sample of the population, more diverse datasets are also required. Additionally, greater effort may be put towards creating algorithms that are resistant to adversarial attacks. Last but not least, research might look into the possible uses of facial recognition algorithms in fresh sectors and create algorithms that can perform more challenging jobs like identifying emotions or forecasting behaviour.

REFERENCES

[1] A Krenker, J Bešter& A Kos,(2011).“Introduction to the Artificial Neural Networks”, Edited Kenji Suzuki, Published by InTech,, JanezaTrdine, Croatia, pp 3-18.

[2] Er. P Kumar&Er.P Sharma, (2014). “ARTIFICIAL NEURAL NETWORKS- A Study”, International Journal of Emerging

Engineering Research and Technology, Volume 2, Issue 2, pp. 143-148.

[3] N Jindal&V Kumar,(2013). “Enhanced Face Recognition Algorithm using PCA with Artificial Neural Networks”, International Journal of Advanced Research in Computer Science and Software Engineering, Volume 3, Issue 6, pp. 864-872.

[4] Mrs. Monika Soni. (2015). Design and Analysis of Single Ended Low Noise Amplifier. International Journal of New Practices in Management and Engineering, 4(01), 01 - 06. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/33

[5] S SudhakarFarfade, M Saberian&L-J Li,(2015). “Multi-view Face Detection Using Deep Convolutional Neural Networks”, International Conference on Multimedia Retrieval, Shanghai, China.

[6] Bishop&C. M. (1995). Neural Networks for Pattern Recognition. Oxford University Press.

[7] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. nature, 521(7553), 436-444

[8] Lin, T. Y., RoyChowdhury, A., & Maji, S. (2015). Bilinear CNNs for fine-grained visual recognition. Proceedings of the IEEE International Conference on Computer Vision, 1449-1457.

[9] Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto&Hartwig Adam, (2017).MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. arXiv preprint arXiv:1704.04861.

[10] Kenneth O. Stanley &RistoMiikkulainen(2002)."Evolving Neural Networks through Augmenting Topologies".

[11] Zhenan Sun et al. (2014)."Gabor-Based Convolutional Neural Networks for Face Recognition".https://www.researchgate.net/publication/326261079_Face_detection_system_for_attendance_of_class’_students.

[12] Hapani, Smit, et al. (2018). "Automated Attendance System Using Image Processing." 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA). IEEE.

[13] Akbar, Md Sajid, et al.(2018)."Face Recognition and RFID Verified Attendance System." 2018 International Conference on Computing, Electronics & Communications Engineering (iCCECE). IEEE.

[14] Tharini, V. J. ., & B. L. Shivakumar. (2023). An Efficient Pruned Matrix Aided Utility Tree for High Utility Itemset Mining from Transactional Database. International Journal of Intelligent Systems and Applications in Engineering, 11(4s), 46–55. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2570

[15] Okokpujie, Kennedy O., et al.(2017). "Design and implementation of a student attendance system using iris biometric recognition." 2017 International Conference on Computational Science and Computational Intelligence (CSCI). IEEE.

[16] Rathod, Hemantkumar, et al.(2017). "Automated attendance system using machine learning approach." 2017 International Conference on Nascent Technologies in Engineering (ICNTE). IEEE.

[17] Siswanto, Adrian RhesaSeptian, AntoSatriyoNugroho, and MaulahikmahGalinium,(2014). "Implementation of face recognition algorithm for biometrics based time attendance system." 2014 International Conference on ICT For Smart Society (ICISS). IEEE.

[18] Chang Lee, Deep Learning for Speech Recognition in Intelligent Assistants , Machine Learning Applications Conference Proceedings, Vol 1 2021.

[19] Lukas, Samuel, et al.(2016). "Student attendance system in classroom using face recognition technique." 2016 International Conference on Information and Communication Technology Convergence (ICTC). IEEE. https://becominghuman.ai/face-detection-using-opencv-with-haarcascade-classifiers-941dbb25177.https://www.superdatascience.com/blogs/opencv-face-recognition

[20] Salim, Omar Abdul Rhman, RashidahFunkeOlanrewaju, and Wasiu Adebayo Balogun. "Class attendance management system using face recognition, (2018)." 2018 7th International Conference on Computer and Communication Engineering (ICCCE). IEEE.