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Review Article

A Smart Attendance System Based on Face Recognition: Challenges and Effects

[1]Muhammad Abubakar Falalu, [2]Ibrahim Umar, [3]Amina Ibrahim, [4]Abdulkadir Shehu Bari, [5]Muhammad Ahmad Baballe*, [6]Aminu Ya'u

[1]Department of Computer Science, Audu Bako College of Agriculture Danbatta, Kano, Nigeria
[2]Department of Building Technology, School of Enviromental Studies Gwarzo, Kano State Polytechnic, Kano, Nigeria
[3]Department of Computer Science, School of Technology, Kano State Polytechnic, Kano, Nigeria
[4]Department of Computer Science, Audu Bako College of Agriculture Danbatta, Kano, Nigeria
[5]Department of Computer Engineering Technology, School of Technology, Kano State Polytechnic, Kano, Nigeria
[6]Department of Architecture Technology, School of Enviromental Studies Gwarzo, Kano State Polytechnic, Kano, Nigeria

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***Corresponding author:** Muhammad Ahmad Baballe
Department of Computer Engineering Technology, School of Technology, Kano State Polytechnic, Kano, Nigeria
ORCID: 0000-0001-9441-7023

Abstract
Modern high technology has significantly advanced thanks to the fourth industrial revolution, and artificial intelligence has made tremendous strides. Facial recognition is one of the most important computer vision jobs in real life, with applications ranging from intelligent services to security and attendance systems.

Keywords: RFID, Artificial intelligence; Attendance system; Facial recognition; Internet of Thing; Mobile Nets.

INTRODUCTION

Today's fourth industrial revolution has achieved an amazing confluence of cutting-edge technology advancements, providing a chance to address global concerns [69]. Attendance is crucial in influencing students' academic achievement in a wide range of real-life and practical systems [1–9]. Systems for nearly automatic human identification are based on time-tested techniques like user IDs, passwords, and fingerprints [1, 2]. But, issues like losing an ID card and forgetting a password become inconvenient. In order to do so, new technologies have been used, such as radio frequency identification systems (RFID) [5, 6, 65, 66, 67] or rapid response (QR) codes [3, 4]. Linear barcode scanners are unable to read QR codes. They need fixed reading distance image processing systems based on cameras. By utilizing the Geolocation information, Sultana et al. [7] presented an Android-based attendance tracking system. To enhance the quality of monitoring, Mahesh et al. in [8] combined a smartphone with a smart classroom built on facial recognition technology. RFID usage is based on physical usage frequency. Obstacles or wave-absorbing materials close to the RFID reader can reduce the quality. Voice, fingerprints, and face recognition are only a few examples of other technologies that use biometric markers to track attendance [9–14]. According to the time duration reports, fingerprints have also been employed in [10–12] to identify individuals and determine the attendance percentage. Due to poor image processing and lighting, face recognition has several limitations in real-world situations [9, 13, 14]. The stability and effectiveness of the attendance quality in the working environment settings are ensured by improved facial recognition algorithms in conjunction with support systems and equipment [13]. The face recognition problem [13–18] stands out since it necessitates high accuracy and good processing speed, research for real-world applications, etc. Despite recent developments in face recognition technology, the widespread application of reliable facial recognition and verification places severe restrictions on current methodologies. How to check whether the preselected facial features from the picture database match the current image's information and whether the person's face is in the system or not. Local binary pattern (LBP) descriptors were utilized by Pawar et al. in [15] to transform the input image into a binary image. Then, a regional feature vector was created by concatenating the descriptors at various resolutions. The histogram feature was determined by computing the histogram density on each block. However, extrinsic factors like input image quality, light, and other variables may have an impact on the feature extraction from histograms. The article used Face Net to calculate

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the separation between face vectors in an effort to lessen this impact. Shebani et al. suggested the modified facial recognition architecture in [16], which combines three- and four-patched LBP with Linear Discriminant Analysis (LDA) [16] and Support Vector Machine (SVM) [18-21] to increase the accuracy of face recognition by encoding similarities between nearby pixel patches. We take into account the issues with little training data as one of them. To satisfy the needed accuracy and frame rate within the constraints of the system resources, the performance of the facial recognition system in particular needs to be optimized. However, due to the numerous multi-layer perceptron's (a network with n (n 2) layers (typically the input is not taken into account): where there is an output layer (the nth layer) and (n-1) hidden layer) which increases the computational volume, previous papers using Neural Network (NN) combined with LDA [22-29] have achieved facial recognition accuracy of more than 95% and processing speed of 4 FPS. Pawar et al., in [15] proposed real-time face recognition with LPB model applying into smart city model with only achieves 80 % accuracy [24]. The facial recognition model was then enhanced by T. V. Dang et al. [28] to raise the accuracy to 87-90%. Moreover, the recognition process has been impacted by feature extraction from the histogram. Convolutional neural networks (CNNs) have thus been created as effective models for image recognition issues needing vast quantities of labeled training data. CNNs can only be used to solve issues with a small amount of training data since calculating millions of deep CNN parameters takes a huge number of labeled examples [25]. Deep Convolutional Neural Networks (DCNNs) enhance facial recognition as a result of the successful implementation of deep learning [26]. One of the most widely used DCNN architectures in computer vision is MobileNetV2 [26, 27]. The Conv2D layer will be replaced by a depth-wise separable convolution layer, which will further improve the efficiency of MobileNetV2's face recognition system by lightening the load on the convolutional network layers. Moreover, the MobilenetV2 output serves as the face detection input for Single-Shot Detection (SSD), which also uses it. For the purposes of this study, the paper makes use of an improved Face Net model built on the MobileNetV2 backbone and SSD subsection, which guarantees resolving the object identification issue and can be used in security or attendance systems with mobile devices that have limited resources while still achieving high levels of accuracy and speed. The following output demonstrates that this is the best model for low-resource mobile and embedded devices: Jetson Mini (128-core MaxwellTM GPU, quad-core ARM Cortex-A57 CPU) [29, 50–64]. Practical examples show that produced face images have a good detection performance with a 95% accuracy and a 25 frame per second inference speed. The model is more effective and quicker than state-of-the-art models, which need more datasets for training and processing and fewer resources in the training model. Ultimately, the IoT and upgraded facial recognition technology were effectively integrated into the smart attendance system [30–36].

SUGGESTIVE METHOD

The automatic attendance system is composed of two primary processing stages. For the best accuracy in identification and attendance, there will be two layers of identification at the user interface layer, the first based on the fingerprint system and the second with the camera system. Data is sent to the second layer for processing once it has been gathered at the first layer. At this time, the data will have been fully calculated. The lecturers will then assess the final grade for each student and save the information to the database at the conclusion of the course. Lastly, an Excel file can be used to import and export the data. The model may be operated on the Jetson Nano 4GB embedded computer using only 5 to 10 watts of power. Developer of the Jetson Nano 4GB, AI Development Board, includes the following: CPU: Quad-core ARM A57@1.43 GHz; Memory: 4 GB 64-bit LPDDR4 (25.6 GB/s); and Storage: 16GB EMMC. GPU: 128-core Maxwell. We can install a workable attendance system with numerous recognition cameras using the advantages that Jetson Nano offers, especially the GPU-based board. This system calls for cameras with sufficient quality and between 25 and 30 frames per second (FPS). The R305 Fingerprint Scanning Module is a product with a compact design, reliable performance, and straightforward construction. Power supply between 3.6 and 6 VDC; USB 1.1 or TTL-UART communication; multi-fingerprint recognition mode; baud rate: 57600 bps; average recognition time of less than 0.8 s; etc. are some of the specifications. It assists in capturing and storing the user's fingerprint identifying data, allowing it to be distinguished from fingerprints. Consequently, to improve the functionality of the attendance system and check identification, we employ the fingerprint scanning module in conjunction with the Jetson Nano. Use the program PYQT5 to create graphical user interfaces (GUIs). This is a Python-created interface for Qt, one of the most well-known and renowned cross-platform GUI toolkits. Then, for learning models, employ some deep learning frameworks, such as Keras, TensorFlow, etc. [30]. The entire data system will be handled on a single thread when the attendance system uses a standard scan module. Yet, a system that combines facial recognition with fingerprinting. Face recognition system using Jetson Nano capable of handling multiple video streams [31]. Jetson Nano is connected to the camera module for storing the acquired camera images. a TV or LCD monitor that is connected to the Jetson Nano as a means of observation. Mobile phones, laptops, and desktop computers may all access the Internet with the Jetson Nano [31–33]. Mobile Nets are built on a simplified design that creates lightweight deep neural networks using depth-wise separable convolutions [37–44]. In comparison to MobileNetV1 [26, 44], MobileNetV2 [37–43] makes improvements to achieve higher accuracy with less input parameters and calculations. Using depth-wise separable convolutions with linear bottlenecks and inverted residual blocks (shortcut connections between bottlenecks) [43], we primarily introduce the key features of MobileNetV2, optimize the loss function, and use the improved model architecture from the Face Net model to illustrate MobileNetV2. Because standard residual architectures have more channels at a block's input and output than at its intermediate layers, MobileNetV2's residual block is the polar opposite of previous residual architectures. To reduce the amount of model parameters, one of the layers has an inverted residual block, and depth-separated convolution transforms are also used. The answer allows for a minor size reduction of the Mobile Net model. Real-time and lightweight networking are becoming more and more important in the age of mobile networks. Nevertheless, due to an excessive number of parameters and computations, many identity networks are unable to achieve the real-time criteria. When compared to other contemporary approaches for resolving this issue, the proposed solution leveraging the MobileNetV2 backbone performs better in the database of face expressions and features. The input channels are expanded by 1x1 point convolution in the MobileNetV2 algorithm. Finally, integrate output features while lowering the size of the network by using linear convolutional integration and depth convolution to obtain linear features from the input. Replacing Relu6 with a linear function after size reduction will allow the output channel size to match the input. When used with SSDs, MobileNetV2 will be very helpful in lowering latency and increasing processing performance. YOLO [14] and Faster-RCNN [46] are two fast and effective object detection features that are shown in the subsection SSD [45, 46], which is one of them. As a result, the subsection SSD extracts the feature map from the MobilenetV2 backbone and adds extra bits to forecast the item. Initiation modules are used in blocks by Face Net to minimize the amount of trainable parameters [13]. This model creates a 128-d embedding vector for each picture from a 160x160 RGB image. Extraction of Face Net features for face recognition. Face Net can be used to vectorize facial features, and the triplet loss function can be used to determine how far apart the face vectors are from one another. To make mathematical comparison and recognition easier, the face will first be represented as a vector [71]. In order to calculate the similarity and difference between the faces we receive for face identification, we must essentially solve the problem of computing the distance between the Triplet Loss vectors. Three parameters make up a triplet; they are the inquiry, a second face image of the subject, and a third, unrelated face image [28, 47, 48]. Face detection and face recognition are the two primary steps in the recognition process. Algorithms used in each procedure vary. In this study, the author employs Face Net feature extraction for face identification and a multilayer convolutional neural network to recognize faces in frames. The MobileNetV2 backbone network is used by the subsection SSD to define the face's box during the face recognition process. Nevertheless, the output of MobileNetV2 will be used as feature maps to base the detection on the input photos, and the last few layers of the network, including FC, Maxpool, and SoftMax, will be disregarded. Finally, using a face image as input, Face Net generates a vector of 128 values that reflect the most crucial facial traits for each individual. This vector is known as an embedding in machine learning. The gap between facial traits is then measured using a classifier to differentiate between various identities. Due to their effectiveness in multi-class classification, support vector machines (SVM) in [18, 19] and K-Nearest Neighbor (KNN) in [50] are two of the most often employed algorithms in face recognition applications. The Face Net model extracts features for face identification after detecting faces in the frame. The Labeled Face in the Wild (LFW) dataset, which contains more than 13000 photos of human faces, is used as the pre-training image database for a multi-layer convolutional network [28, 47, 48, 49]. The photos of 150 tagged subjects from three classrooms make up the attendance training data. 50 students from each class will upload their photos for face recognition training. The direct face view image with all of the feature information contains the majority of the faces in the dataset. Using a larger face dataset, we assess the Face Net model based on the MobileNetV2 backbone network and SSD subsection and contrast it with models like MTCNN employing O-net, P-net, and R-net in [7, 43, 48]. Rectinaface model built using the respective R512 and R50 backbones [47]. All of the models in [7, 43, 48] achieve the same high accuracy at a low frame rate. Similar to the Rectinaface model's result based on MobilenetV2, Particularly, the Face Net model's result based on the attendance system's backbone MTCNN [28] is approximately 87-90%. We use the faces of 14 randomly selected students to assess the Face Net model's performance in the face recognition method based on MobilenetV2-SSD. The model's accuracy ranges from 91% to 94%. The experimental outcomes, which were based on the MTCNN backbone, outperformed Face Net significantly [28]. The new Face Net model is more effective and quicker than the previous state-of-the-art models, which require larger datasets for training and processing, based on the suggested experimental approach, which uses smaller datasets and fewer resources in the training model. The intended system exemplified two crucial characteristics in relation to its capacity to enhance the veracity of the attendance, as follows: Use face recognition for automatic attendance verification first because it is the least evasive and just needs simple acquisition tools. Second, integrate highly mobile devices with advanced mobile devices that have constrained resources (such as constrained RAM and on-device storage) with short datasets and fewer resources in the training model [68].

Pros of Facial Recognition

Technology like facial recognition can help society in various ways, such as by minimizing human interaction, enhancing safety and security, and preventing crimes. Consider some advantages of facial recognition:

1. Helps find missing people
2. Protects businesses against theft
3. Improves medical treatment
4. Strengthens security measures
5. Makes shopping more efficient
6. Reduces the number of touchpoints

7. Improves photo organization [72].

Cons of Facial Recognition

A cutting-edge technology called facial recognition has the potential to alter our future. However, the introduction of this new system into society carries some dangers and implications, just like every invention.

1. Threatens privacy
2. Imposes on personal freedom
3. Violates personal rights
4. Data vulnerabilities
5. Misuse causing fraud and other crimes
6. Technology is still new
7. Errors can implicate innocent people
8. Technology can be manipulated [72].

Conclusion

In order to reduce the model size and compute volume, this paper uses a Face Net model built on the foundation of MobilenetV2 with the subsection SSD to detect faces using depth-separated convolutional networks. The results are astounding. By contrasting various retinal models and the MCTT backbone, the authors experimented with and assessed the proposed model. The SSD in conjunction with the MobileNetV2 backbone has enabled accuracy of roughly 99% in simulated studies and 91-95% in real-world applications using the same dataset as Wider Face. A frame rate of 20–23 (FPS) substantially speeds up the procedure. The revised Face Net model is more effective and quicker than the previous state-of-the-art models, which need larger datasets for training and processing. It also requires fewer resources in the training model. In addition, the deep learning-based solution might be able to maximize the resources of a variety of low-capacity hardware systems. The facial recognition system's effects and difficulties are examined.

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