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Face Recognition Smart Attendance System

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Abstract

Facial recognition has emerged as a key area of research in recent years because of its vital role in biometric authentication for numerous applica-tions, such as access control and attendance management systems. Effective at-tendance management is essential for organizations, but traditional methods can be challenging and time-consuming. Speech recognition, RFID, biometrics, and eye tracking are just a few of the many automatic identification techniques. Face recognition is one of the most widely used biometric methods for identifi-cation verification. This research presents a deep learning-based facial recogni-tion attendance system based on convolutional neural networks. It employs transfer learning using three pre-trained convolutional neural networks that are further trained on the dataset. These networks demonstrated remarkable per-formance, achieving high prediction accuracy while maintaining a reasonable training time.

Keywords: Face Recognition; Smart Attendance.

How to Cite This Article

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Introduction

Every organization requires an attendance management system in order to track staff attendance, whether manually or automatically. Maintaining standards of quality in educational institutions and evaluating student performance depend on the daily at-tendance of students being documented. Researchers have placed a lot of emphasis on face recognition (FR) as one of the most significant uses of artificial intelligence and computer vision.

Deep convolutional neural networks have significantly advanced facial recognition in recent years. But prior to 2014, FR used manual-designed features and conventional techniques. Eigenface, one of the first methods, converted grayscale face photos into one-dimensional feature vectors and then projected them into a lower-dimensional space using Principal Component Analysis (PCA). This allowed for the tighter feature distributions of comparable faces. By utilizing Euclidean distance to compare new faces to known ones, the algorithm was able to identify them. The major drawback of Eigenface, which concentrated only on maximizing variance without taking facial categories into account, by adding class labels into the feature extraction procedure [1-2]. Calling out names or signing paper records are two time-consuming and securi-ty-risky traditional attendance tracking techniques. Numerous automated identifica-tion systems depend on traditional methods such as ID cards, password authentica-tion, or fingerprint scanning; nevertheless, these approaches have disadvantages, such as the potential for lost ID cards or forgotten passwords. A safer and more effective substitute is facing recognition, which guarantees precise identification verification and smoothly keeps track of attendance records. Because of its accuracy in identifying and validating people, FR-a rapidly developing field-is essential to security applica-tions [3-4].

A model that has been trained for one task can be modified for another using the potent machine learning technique known as transfer learning. It is extensively uti-lized in deep learning for natural language processing and computer vision, enabling pre-trained models to speed up the creation of intricate neural networks. Since many real-world problems need extremely complex models and include large volumes of labelled data, transfer learning improves model correctness, minimizes training time, and maximizes performance. Additionally, it helps developers to enhance models for difficult jobs and integrate various applications effectively.

In this paper, the face recognition technology is investigated. The design, imple-mentation, and practicality of an AI-powered facial recognition attendance manage-ment system are the main topics of this study. It tackles important issues like accura-cy, computational efficiency, privacy issues, and the effects of masked facial recogni-tion. It analyses the impact of model architecture and data distribution on system per-formance through a great deal of testing. Additionally, demonstrate real-world uses of facial recognition technology in attendance control, showcasing how it may improve security and efficiency in both professional and educational settings.

History of Face Detection System

ALEX NET

One of the most popular neural network architectures available today is AlexNet. Millions of photos have been used to train it to categorize items into several groups, such as faces, fruits, cups, pencils, and animals. After processing an input image, the network provides a label for each category along with likelihood scores. RGB images with dimensions of 227 × 227 × 3 can be entered into it [4], [5]. Figure 1 shows the architecture of Alexnet whereas the output is at D1 along with M2.

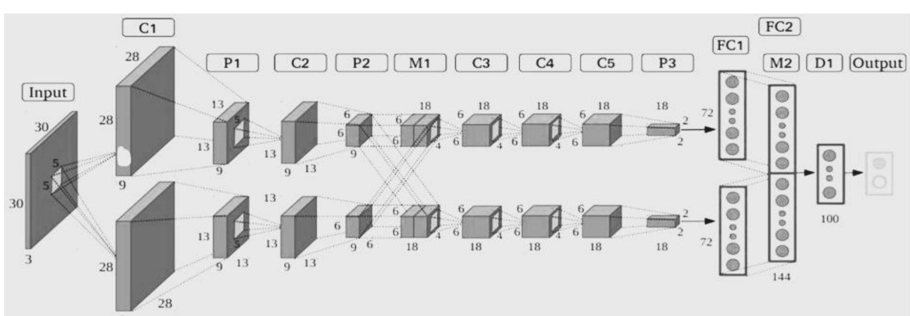

Fig. 1. *Shows the architecture of Alexnet*

GOOGLE NET

In addition to five pooling levels, the Google Net topology has 22 deep layers. Nine initiation modules are layered linearly in total. It also makes use of a 1x1 convolution filter. Due to layer reduction and parallel network implementation, the net has very strong computation and memory efficiency, and its model size is smaller than others [6]. the architecture of Google Net whereas the output is considered from C2 along with P3.

SQUEEZE NET

An 18-layer deep convolutional neural network called Squeeze Net was created for effective picture classification. Images can be categorized into 1,000 distinct item categories using the pre-trained model. It can acquire intricate feature representations because it has been trained on a wide variety of images. The ability of Squeeze Net to build a compact neural network that works well on fewer datasets, uses less memory, and is simpler to send over a network is its main benefit shows the Squeeze Net de-sign whereas output is taken from FC.

Literature Review

Face identity has been studied by numerous research organizations using a variety of methods. One current method combines a Self-Organizing Map (SOM) classifier with a face recognition technique based on features taken from Discrete Cosine Transform (DCT) coefficients. MATLAB was used to evaluate this approach on participants with various facial expressions. After 9 consecutive trials, the system's identification rate was 87.36%, requiring about 850 training epochs. This system's smaller feature area makes it ideal for real-time, low-cost hardware implementation.

A facial recognition-based deep learning attendance system. Their approach uses contemporary methods, including CNN-based face embedding generation and a CNN cascade for face identification. The algorithm demonstrated an overall accuracy of 95.02% when evaluated on a small sample of real-world employee face photographs. The suggested model can be modified for application in several other systems.

By combining two deep learning models, multiple works Cascade for the Convolu-tional Neural Network (MTCNN) for face identification and Center-Face for recogni-tion suggested an automated method for university classroom attendance. Figure 2, represents the face recognition System that approach uses vast experimental data to identify three classroom disciplinary violations: early leave, tardiness, and absence. An attendance record that details each student's presence and academic progress is automatically created at the end of each lesson.

The system is quite effective; it can identify faces with high accuracy in less than 100 milliseconds each frame. Its accuracy rate is 98.87%, its false positive rate is 93.7%, and its true positive rate is less than 1/1000.

In order to recognize faces in input photos, we created a CNN-based facial recogni-tion system that uses the Viola-Jones face detector [7-9]. After that, the system auto-matically extracts and recognizes face characteristics using a CNN that has already been trained.

To increase the number of photos per person while simulating different lighting con-ditions and noise levels, a sizable library of facial photographs was built and en-hanced. For deep face recognition, an optimal pre-trained CNN model with hyperpa-rameters chosen through experimentation was also employed. With an overall accura-cy of 98.76%, the technology proved to be effective in biometric authentication. The system is quite effective; it can identify faces with high accuracy in less than 100 milliseconds each frame. Its accuracy rate is 98.87%, its false positive rate is 93.7%, and its true positive rate is less than 1/1000.

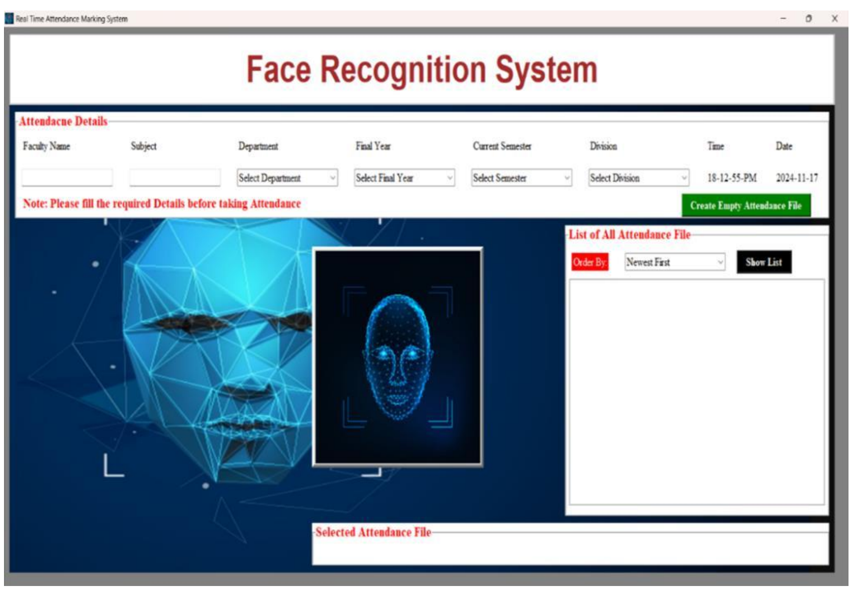

Fig. 2. *Face Recognition System*

Method

Data gathering, pre-processing, augmentation, CNN training and validation, and sys-tem testing are the steps in the suggested methodology.

Data Collection

The 200 photos in the dataset were taken using the MSI Desktop front-facing camera, which has an 8-megapixel sensor and an f/2.1 lens. There are ten different classes in the collection, and each class has twenty photos. Figure 3 shows the dataset which includes the classes correspond to both genders.

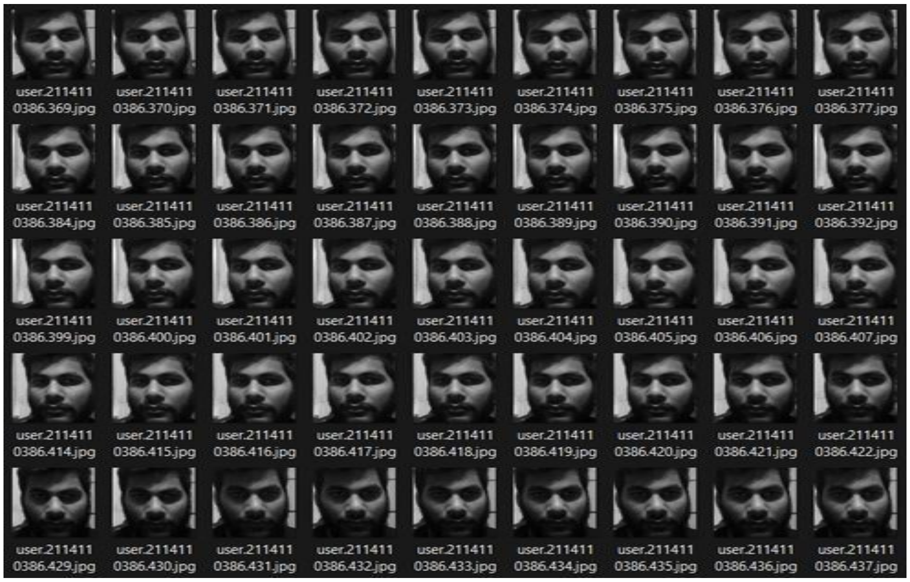

Fig. 3. *Dataset*

Data Formatting

The JPG format is used to store the gathered data, and the image sizes range from

3.00 MB to 4.00 MB. The photos were adjusted in accordance with the particular input size requirements of each neural network. GoogleNet analyzes photos of 224 × 224 pixels, whereas SqueezeNet and AlexNet require images of 227 × 227 pixels. Every picture was taken in RED GREEN BLUE, which makes it easier to extract the characteristics required for precise facial identification.

Data Augmentation

By producing slightly modified copies of the current data or producing new synthetic data from the original data, a process known as data augmentation is used to expand the size of a dataset. By regularizing the model, this procedure helps to avoid overfit-ting during training. Geometric changes, flipping, color tweaks, cropping, rotation, noise injection, and random erasing are just a few of the alterations that may be used in deep learning data augmentation to improve the dataset [8]. We used data augmen-tation throughout our training process by taking pictures from a variety of viewpoints, settings, circumstances, orientations, locations, and illumination levels. We used two distinct data augmentation methods—rotation and scaling—after integrating the da-taset into the network. Random scaling was applied within a factor range of 1 to 2, and each picture was randomly rotated within an angle range of -90 to 90 degrees.

Choice of Pre-trained Data

Choose three networks—SqueezeNet, AlexNet, and GoogleNet-to train the convolu-tional neural network on our dataset. During distributed training, SqueezeNet, a small CNN, requires less communication between servers. Additionally, because of its re-duced size, it is better suited for implementation on field-programmable gate arrays (FPGAs), which are devices with limited memory. However, even with fewer training photos, AlexNet is renowned for its ability to transmit learned characteristics effi-ciently. One of the first deep convolutional networks to attain notable accuracy was AlexNet, which was created to enhance performance in the ImageNet challenge.

Dropout layers, in which connections are randomly discarded during training with a probability of p = 0.5, are used by AlexNet to solve the overfitting issue. After a lot of testing, this dropout rate was selected because it offered the optimal trade-off between the network's training options and parameters. Dropout doubles the number of itera-tions required for convergence while enabling the network to escape bad local minima and preventing overfitting.

Result and Discussion

To guarantee efficient training and data validation, SqueezeNet has to be trained across 30 epochs, with 12 iterations each epoch. It reached a validation accuracy of 98.33% after 360 iterations. It took 26 minutes and 53 seconds to complete the full training. Validation was carried out after every ten iterations to make sure the system was sufficiently trained and to avoid overfitting. Figure 4 represents the frequency distribution.

Likewise, it took 30 epochs, with 12 iterations each epoch, to train GoogleNet. It achieved a validation accuracy of 93.33% after 360 iterations, Recognize Output Sta-tus is given in Fig. 5. Google Net took 39 minutes and 21 seconds to train. Validation took place every ten iterations, just as SqueezeNet, to keep an eye on system perfor-mance and prevent overfitting.

It took longer to train AlexNet, requiring 60 epochs with 12 iterations each. The net-work was well-trained, as seen by its 100% flawless validation accuracy after 720 iterations. AlexNet took 76 minutes to train in total, which was a lot longer than the other two networks. In order to avoid overfitting, validation was also carried out every ten iterations. A single-core CPU operating at 1.8 GHz with 8 GB of RAM made up the machine utilized to train all three networks. The starting learning rate, maximum iterations, and single CPU configuration were the same for all three networks, as seen in the only difference being the number of epochs. The model score is mentioned in Fig. 6.

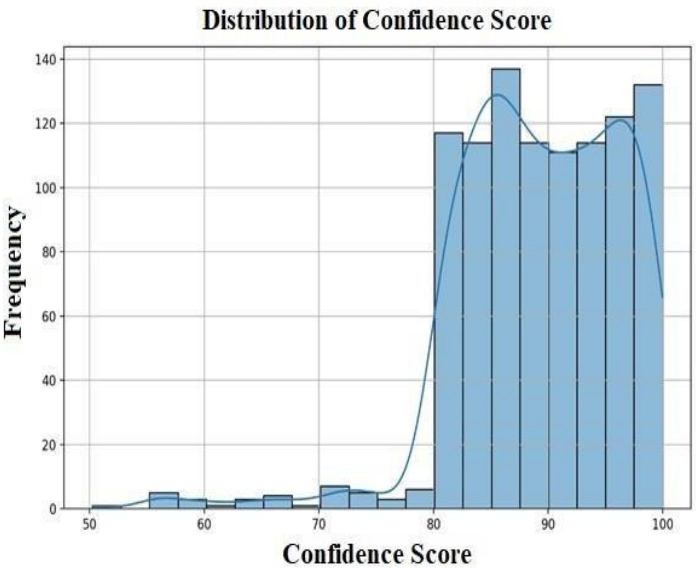

Fig. 4. *Frequency Distribution*

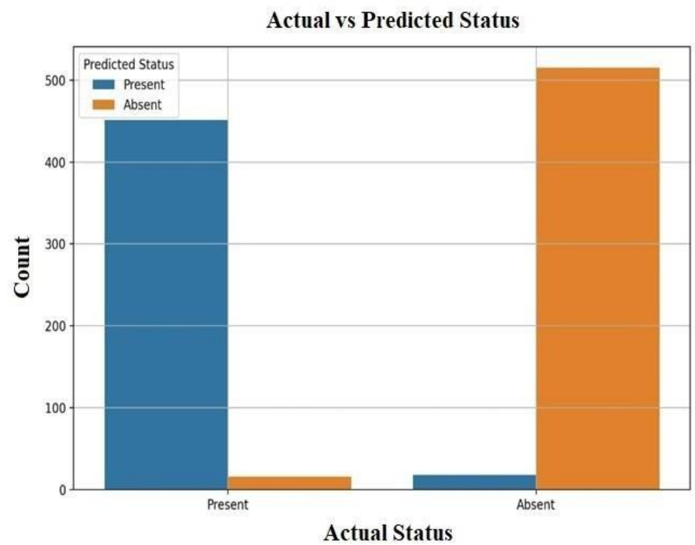

Fig. 5. *Recognize Output Status*

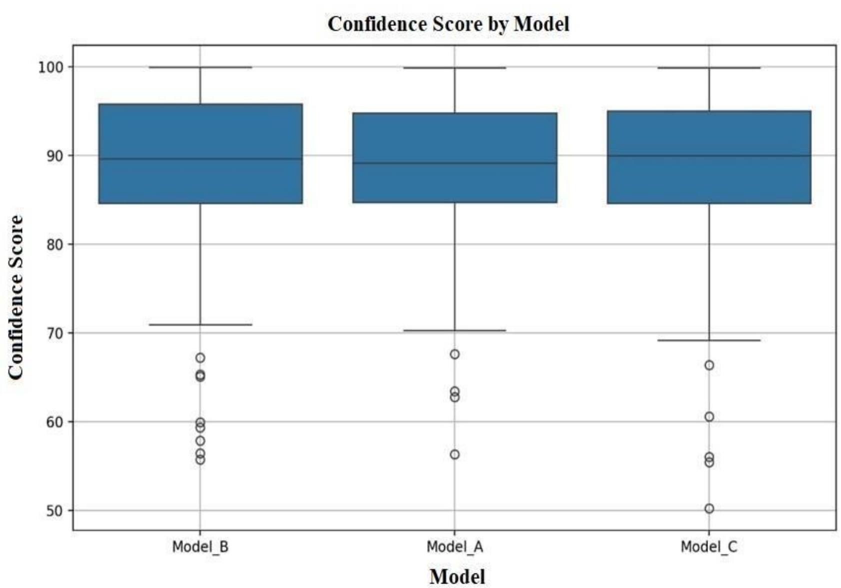

Fig. 6. *Model Score*

All three CNN models performed exceptionally well in identifying faces with a high degree of prediction confidence when evaluated on unseen photos from the 10 distinct classes. The confidence level of each model in predicting the relevant labels is shown by the percentage that is shown above in the photos. The model's successful identifica-tion of the image is indicated by a very high confidence level. The outcomes attained by SqueezeNet, GoogleNet, and AlexNet.

Except for the number of epochs, kept the initial learning rate, maximum iterations, and single-core CPU configuration constant for all networks in order to analyze the results. Despite requiring the longest training time, AlexNet had the greatest valida-tion accuracy, making it the best network for training, according to the data. With an accuracy of 98.33% and a comparatively short training duration of 26 minutes.

Conclusion

In this work, an AI-powered face recognition attendance management system is de-veloped using computer vision and machine learning. The goal of the project is to address the shortcomings of traditional attendance systems by providing a more effi-cient, accurate, and automated substitute. The system incorporates sophisticated face detection and recognition algorithms to streamline attendance tracking and improve user convenience and security.

During testing in a range of real-world scenarios, the proposed system's ability to manage many users and operate in a variety of lighting and environmental conditions was proven. The results show that using facial recognition software significantly re-duces the likelihood of errors and the amount of time spent on human attendance procedures. Despite the promising outcomes, this technique also highlighted certain limitations, such as the need for continuous illumination and occasional misidentifica-tion caused by angle or facial obstruction. Future advancements could focus on im-proving accuracy, expanding the system's flexibility to accommodate different situa-tions, and exploring additional use cases such as real-time security monitoring or integration with classroom management systems.

All things considered, the AI-powered facial recognition attendance system offers a scalable solution that can be utilized in educational institutions, enterprises, and other settings, and it is a step forward in automating administrative tasks. The future devel-opment of attendance management systems and other related applications will be significantly influenced by these technologies as AI advances.

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