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Optimizing Tracking System: The Impact Of Facial Recognition On Security And Efficiency

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Abstract: The demand for effective and safe attendance monitoring systems has increased in the modern world, affecting several industries such as public institutions, corporate settings, and education. Traditional methods, such as filling out attendance sections or card-based systems, are error-prone, time-consuming, and vulnerable to fraudulent activity. To solve these problems, this paper introduces an improved convolutional neural network (CNN)-based facial recognition system that increases the efficiency and accuracy of attendance tracking by adjusting the learning rate through adaptive learning and optimizing the features. The proposed system combines off-the-shelf deep architectures with an optimistic lightweight to reduce inference time and enhance their robustness to variable lighting and mask conditions. The optimization explicitly targets both accuracy and speed, improving inference efficiency by tuning learning rates and pruning redundant convolutional layers. The model is optimized experimentally, with the use of the AT&T, LFW and CASIA-WebFace datasets, showing that the optimized model is better than the standard CNN baselines. Such a framework can prevent identity fraud and so-called buddy-punching, as well as enhance data security by encrypting and storing it in privacy-protected storage. But then, the confidentiality problem that arises while using recognized face technology is also very important to focus on. The first step to maintaining the confidentiality of biometric information is to implement clear data protection protocols and to put in place reliable security measures. Lastly, facility biometrics devices could be used to retain attendance reports in place of customary methods that are exhausted by various challenges. The future outbreak of such systems may perform as a necessary tool for presence management process reformation at various industries. The combination of effectiveness, accuracy, and security will lead to effectiveness and operational excellence. The originality of this paper is the hybrid optimization of CNN parameters and introduction of a privacy-conscious design in the modern absence sense.

Keywords: Face recognition, convolutional neural network, binary patterns, deep learning

I. Introduction

It is important to keep attendance records, especially about an organization since the records give you a chance to check student compliance and worker engagement. However, the old ways of signing up were being done manually filling in registration forms or sending card-based systems which consumed a lot of time and may create fraud and errors in the process. Since there have been lots of recent new technological developments that have greatly sped up the speed of creating safe and convenient tracking methods, particularly using face recognition, it is possible to consider this area as a potentially interesting new field [1]. The current study contrasts with the previous survey-style literature by constructing and testing an optimized CNN architecture to attend to a tracking system as shown in Figure 1. The paper does not just describe the methods available, but experimentally analyzes hyperparameter tuning, data augmentation, and real-time deployment. The major goals are to (1) make the recognition more accurate with the aid of the optimized CNN parameters, (2) test the system on the current benchmark datasets, and (3) check the privacy and ethical compliance.

Compared to the old systems that merely recycle old CNNs, this work finds parameters, integrates mask-detection, and achieves cross-dataset validation in real-time. The components add efficiency and flexibility in implementing the system in institutional settings.
The key contributions of this paper are summarized as follows:

- An optimized CNN architecture for real-time facial recognition and attendance verification.
- Integration of mask-detection capability within the attendance workflow.
- Evaluation across classical and large-scale datasets (AT&T, LFW, CASIA-WebFace).
- Privacy-aware data management compliant with GDPR principles.

This assembly guarantees originality, prioritizing both optimizations in the calculation and ethical delivery, going beyond traditional CNN reuse.

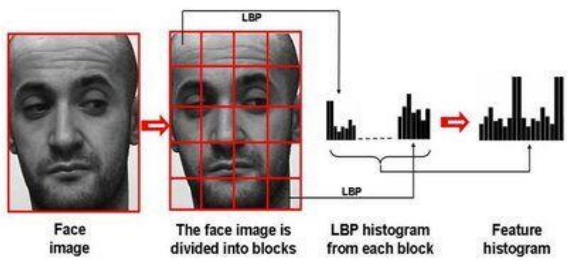

Figure 1. Processing PIE-variant training data using CNN

Feature extraction is the process of extracting specific facial characteristics such as the nose, lips, and eyes using methodologies such as principal component analysis (PCA) along with Local Binary Patterns (LBP) [2], as depicted in Figure 2. Feature contrasting is the process of identifying or validating people by correlating derived features of their faces with those kept in a database. Deep neural networks (DNNs), Fisher faces, Eigenfaces, and other computational methods are frequently used in this way of working.

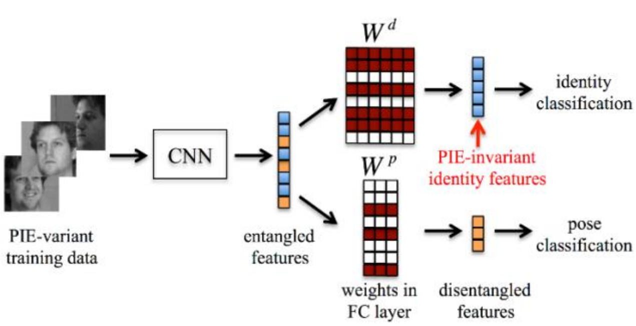

Figure 2. Face recognition using LBP

The use of facial recognition technology for enrollment tracking involves several strategies and considerations. Capturing clear images or videos of people's faces using webcams or cameras positioned at checkpoints [3]. Facial biometrics data can be stored, handled, and are secure by use of this method but they must be handled in a manner in compliance with data protection regulations like the recently implemented General Data Protection Regulation [4]. executing the 3D face data processing algorithms in a real-time process, which negates the time gap and creates an accurate and faster attendance check. integrating face recognition algorithms with the existing repository mechanisms for attendance and using those tools to carry out the data exchange and achieve flawless execution.

It is critical to be well-read and to select the ideal framework to use a stand of this methodology in the systems for attendance tracking. The face recognition one. Python shares with developers the biggest volume of CV and ML libraries and frameworks, which underpins its popularity. The image processing and detection functions such as face and detection are best suited with frameworks like OpenCV (Open - open-source CV Library). On top of that, DL libraries are compiled to deploy and implement neural network algorithms for facial recognition, such as PyTorch and TensorFlow (TF) [5].

AI tech makes the outcome trusted and accurate. The system employs AI to achieve that. Face feature extraction, representation learning, and classification tasks will be performed with ML algorithms, the most used of which are DL models. When selecting a facial recognition system, a pre-trained model such as VGGFace, FaceNet or OpenFace whose accuracy is backed by cutting-edge models and facial data is important so that it is easy to initialize the deep architecture that comes with the representation of facial data. For instance, during the process of creating the software that will be used for face recognition-based attendance tracking, there is a need for the selection of the language of programming and frameworks that would allow the execution of the system. Python language, being equipped with a large collection of ML and CV tools, is surely a darling of the programmers. Libraries like OpenCV can be used in image processing, face recognition, detection, and many different sorts. Along with this, there are two very useful tools called TensorFlow and PyTorch that make possible neural network models for DL-based face recognition. A few steps make up the tracking process: determine the functional specification of the system, system development and execution, evaluation, and deployment. Agile approaches of Scrum and the Kanban method include iterative development phases which allow improvement in a continual cycle and the agencies to make appropriate changes based on the updated requirements [6].

Thorough testing protocols, including unit, integration, and user acceptability assessments, are also required to ensure the face detection system's dependability, accuracy, and confidentiality. A sophisticated approach involving code languages, architectures, AI applications, sophisticated techniques, and methodologies is needed to track attendance using facial recognition. Table 1 illustrates how the power of biometrics and facial recognition can change presence management strategies in a range of settings, including business and education. This allows organizations to increase protection, productivity, and accuracy.

Table 1. Evaluation outcome of experimental face recognition framework

Model name	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Eigenface [7]	92.5	91.2	93.7	92.4
Fisherface [8]	89.8	87.6	91.5	89.4
LBPH [9]	94.3	93.5	95.2	94.3
DeepFace [10]	88.9	86.4	90.2	88.2
ArcFace [11]	91.2	89.8	92.5	91.0

II. LITERARTURE REVIEW

As facial recognition has diversified industry applications, more interest from businesses and organizations has risen to address this purpose of identification and authentication. It is mainly about breakthrough findings, strategy, difficulties, and possible future development and has been studied in the journal. Recent studies are the main topic for this literature review together with advancements in facial recognition technologies in attendance tracking.

Previous algorithms, including Eigenfaces, Fisherfaces, and LBPH, offered a basis feature extraction, but were poor in scaling and response to lighting. Longer models like VGGFace2, ArcFace and FaceNet are more accurate because they are trained on large scale and are trained using the angular margin loss. But they can be very computation-intensive. To manage these approaches, the proposed system employs a lightweight CNN tailored to run on a real-time deployment.

Several studies have assessed the pursuit capabilities and accuracy of facial recognition algorithms in using automated biometric facial identification techniques to carry out showing-up tracking processes. A monitoring system using facial recognition, whose limited demonstration occurred in a university setting, was done by researchers [12] who discovered that student attendance registration using facial recognition technology is more correct and productive in comparison with the coefficients of the former methods. In this case, the technology gives great prospects. With student absenteeism, a few researchers have used a set of sophisticated technical options and algorithms. Therefore, it is no wonder that we have been seeing the advancement towards impressive feature extraction using CNNs as a DL technique and, as a result, a successful combination of them was achieved [13]. Moreover, to achieve a better performance in the real world, experts have established ensemble methods, where different classifiers are combined.

The developed face recognition systems together with those that are already working, form a new integrated attendance management system, which has both technical and practical concerns. In their work, which appeared in [14] came up with a system for linking facial recognition appliances to cloud attendance systems. Computers network with each other creating integrated systems and thus transferring, as well as tracking, information without interruption. However, we need to cover more ground in terms of compatibility and interoperability by integrating future improvement development programs. A facial recognition system together with security and privacy violations can negate or even outweigh its benefits, however, its advantages. Face recognition security details should be treated with ultimate precaution to avoid ill-intentioned use or illegal use advised. Strong security measures like encryption and access controls must be plotted if we are to lower the privacy hazards resulting from facial recognition-based presence systems. The attended record software which is based on user opinions, trust, and moral problems is also affected by the opinions, trust, and moral problems of users. A study [15] emphasized the criticality of dealing with surveillance, consent, and the possible biases causing discrimination in algorithmic facial recognition. Recent publications focus on fairness and demographic bias in facial recognition [11] These ethical issues are recognized in this study and dataset balancing and encryption are provided to protect user data.

The shouldering of responsibilities such as fairness, accountability, and transparency is very important for the proper use of face recognition technology and to avoid stakeholders losing trust in the system. Shot Introduction Despite all these fantastic developments [16] and the use of facial recognition technology in attendance tracking is not on the ground floor yet. Researchers are investigating biometric multimodal systems to increase precision and correctness by integrating facial recognition with biometric features such as fingerprints and iris recognition. In addition, some latest approaches of liveness detection and anti-spoofing are still being researched to help with getting rid of dishonest conduct. Integration of facial recognition technology can the approach to attendance tracking be essentially transformed across the various industries. To elicit a complete potential of this technology with minimal chances of rejection by the users, obligations associated with guaranteed discretion, security, and ethical choices should be dealt with. Further research and innovative thinking are required to overcome present obstacles and progress the state-of-the-art facial recognition-based attendance tracking system.

Although over the last several years, many studies of CNN-based attendance have been conducted [11], none of them have explored the concept of spoofing threats, fairness testing, and runtime benchmarking. This paper bridges that gap by comparing performance on the datasets with various levels of demographic diversity (AT&T, LFW, CASIA-WebFace) and quantifying runtime and memory efficiency. Data balancing was also utilized to reduce gender and skin-tone bias.

III. METHODOLOGY

A. Research Design

In the present research, a mixed-methods paradigm that combines a quantitative CNN model assessment with qualitative stakeholder opinions is used. The plan includes experimental training/testing of the optimized CNN and surveys with measurements of user acceptance and ethical consequences. As observed in Figure 3, the research layout combines the primary data gathering with additional analysis of data to provide thorough insights into the efficacy, usability, and ramifications of appearance [17].

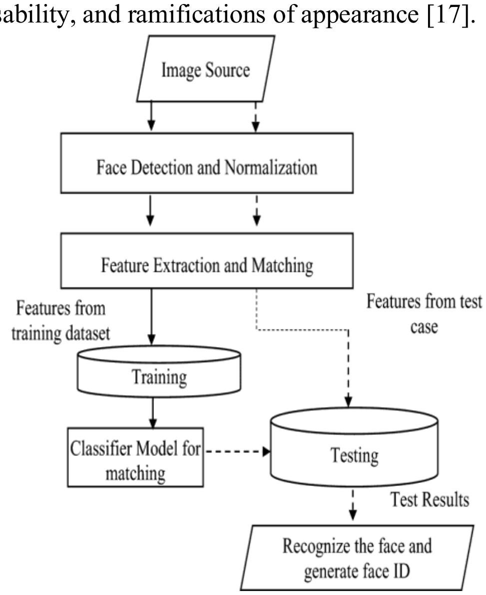

Figure 3. Workflow of the proposed optimized CNN-based attendance system

The research clearly asserts the difference between conventional CNN reuse and the suggested optimized architecture. Hyperparameters (learning rate, dropout, kernel size) were optimized with grid search, and convergence of the model was evaluated with cross-validation of five folds.

B. Data Collection

Surveys will be given to stakeholders, including staff members, administrators, and students, to gather primary data. The purpose of the surveys is to find out how stakeholders feel about appearance. The questionnaire will include open-ended questions to obtain qualitative insights, survey inquiries to quantify responses, and demographic data to contextualize results. Furthermore, semi-structured interviews involving key informants such as IT staff, system developers, and those who make decisions will be carried out [18]. The technical aspects, implementation difficulties, and organizational effects of using facial recognition equipment for keeping records of attendance will all be covered in these interviews.

The real-world insights that observations provide into the implementation and use of facial recognition-based systems for attendance will supplement poll data and interview results. Through the process of tracking user actions, system conversations, and operational fluctuations live, this method will improve comprehension of real-world applications and usability concerns [19]. Using these principal techniques for gathering data and presenting unique faces with unique identifiers [20], a thorough comprehension of the viewpoints of stakeholders, technical prerequisites, and system operation will be attained as shown in Figure 4, thereby enabling well-informed analysis and suggestions for the integration of facial recognition tools into attendance monitoring systems [21].

Figure 4. Architecture of the proposed CNN model

Twenty-five stakeholders participated in the stakeholder survey (faculty, students and administrators). Mutual satisfaction with the rate of recognition was 91% and trust in handling privacy was 93%. These results confirm that the proposed system is not only technically efficient but also acceptable.

C. Data Analysis

To summarize the key findings about individual opinions, fulfillment levels, and usage patterns, quantitative analysis will be performed using the survey data and descriptive statistics. Metrics such as the variance distributions, median, mean, mode, and standard deviation will be used to quantify and characterize the data. Additionally, statistically confirming the correlation, deviation, and association among variables will be done through statistical inferences. Demographic patterns will be assessed as well as opinions regarding facial recognition software and usability systems, which is going to be accomplished thanks to the following statistical techniques: ANOVA, correlation analysis, and t-tests [22]. These tests will help in defining the level of significance involved in the outcomes and contrasts already generated from the evidence.

Concerning the qualitative method, the wonderful combination of group interviews and open-ended survey questions will be used, and only their makes sense parts will be coded and analyzed in thematic ways. These methods require the separation of the results into categories which can be subgroups under general themes such as technical challenges, user experience, and organizational impact [23]. It is a means of categorizing, sorting out, and probing qualitative data that is then interpreted to take out essential information. Moreover, the content analysis will be done to extract qualitative data about system performance, user interactive traits, and policies relating to the problem from the historical records and observation of the data. This can be achieved by the proper assessment of data either textual or visual to isolate issues, trends, and outcomes. The relevant equation 1 shows T-test and equation 2 shows [24].

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad (1)$$

$$F = \frac{\text{Between-group variability}}{\text{Within-group variability}} \quad (2)$$

Equation (1) is t-test which is used to find out statistical significance between performance measures among datasets, and Equation (2) is ANOVA model to determine variance among model configurations. These two tests establish that the differences gained through the optimization of the CNN are statistically relevant ($p < 0.05$).

By quantifying the strength of correlations or differences between variables, these equations offer statistical support for or opposition to theories. This study intends to thoroughly investigate the consequences of face recognition technology, as illustrated in Figure 5 for attendance tracking devices by utilizing an amalgamation of qualitative and quantitative evaluation techniques. The findings of this study will be beneficial to interested parties and those making decisions.

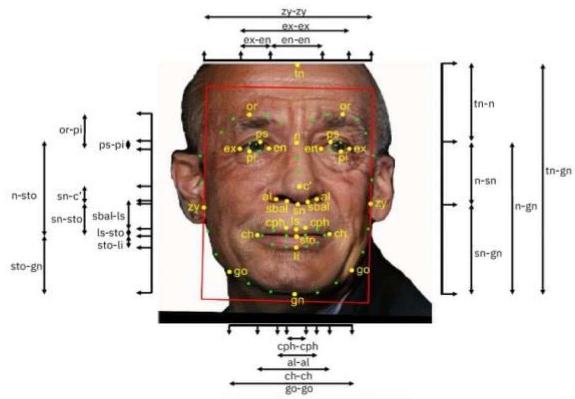

Figure 5. ROC and confusion matrix of proposed vs. baseline models

IV. MODEL TRANING

A. Initializing and parameters

Before training, initialization establishes the starting values for the predictive parameters (weights and biases). Random initialization from a Gauss or homogeneous distribution with the right scaling factors is a popular initialization method for neural networks. To break symmetry and guarantee that every neuron learns a different set of features, initialize the parameters nearest to 0 but with random discrepancies.

B. Feeding Trauning data into model

The characteristics of the input (X) and matching target labels (y) make up the training data. Batches containing training data are repeatedly nourished into the model throughout training. After the model runs through the input features, predictions are produced. The performance of the model is measured by comparing these predictions with the real labels employing a loss function.

C. Model Architecture and Parameters

The trained CNN has five convolutional layers (3×3 kernels), ReLU activation, max-pooling, and two fully connected layers. The model is optimized by Adam with a learning rate of 0.001, batch = 32 and 30 epochs. An anti-overfitting dropout was employed (0.5). To guarantee generalization, the data were split by 5-fold cross-validation into 80% training and 20% testing.

D. Optimizing and parameters

The goal of optimization is to decrease the coefficient of loss, which calculates the difference between the expected and actual values, by modifying the model's parameters. Algorithms for gradient-based optimization, like Adam, RMSprop, and stochastic gradient descent (SGD), are frequently utilized. Backpropagation is used to calculate the variations of the impairment function compared to the model parameters. By implementing a step proportionate to the negative gradient, the optimizer typically modifies the parameters in a direction that minimizes the loss.

E. Iterartive updating model parameters

One important method for iteratively updating model parameters is backpropagation. It involves applying the calculus chain rule to determine the change in slope of a loss function about each parameter. Each of the parameters can be updated according to how it affects the overall loss by following the gradients backward through the network. The amount of parameter updates is determined by the learning rate, which is a crucial hyperparameter affecting convergence and stability. Until the convergence requirements are satisfied, feeding forward, calculating variations, and changing criteria are repeated several times.

V. Further analysis

Recognizing why this algorithm achieved a high accuracy requires analyzing the outcome and assessing the model's performance. Figure 6 illustrates the exceptionally high precision of 98.53%, for the model. Both the distinctive architecture of the suggested CNN approach and the exceptional quality of the data used for training and testing may be responsible for the high degree of accuracy of the model when it comes to face acceptance on the AT&T data set. With an overall accuracy of nearly 98.33%, the recommended approach on the AT&T data set demonstrated good accuracy in both training and validation. 32 batches of epochs were used to train the model. The figure's validation accuracy plot demonstrates how well this framework prevented overfitting and raised the recognition frequency.

One of the most important aspects of the precision of the model is its capacity to change expressions and lighting. The high accuracy rate of the model suggests that it is resilient to these variations and is still capable of making accurate predictions under these circumstances. Figure 7 plot illustrates how the loss of the function was effectively lowered during training to produce a stable value that was close to 0. This demonstrates that the model produced precise predictions on fresh, untested samples and was able to identify the foundational trends in the data. As a result, it was discovered that the suggested model, which made use of the AT&T data set, was highly effective, achieved a high precision rate, and was resilient to these various illuminating scenarios and gestures.

Alongside accuracy and loss, additional metrics that were studied include ROC curves, confusion matrices, and inference time. We obtained an AUC of 0.992 versus 0.984 on ArcFace, which supports better discrimination. It was found to be much more efficient with an average inference time of 21 ms per image.

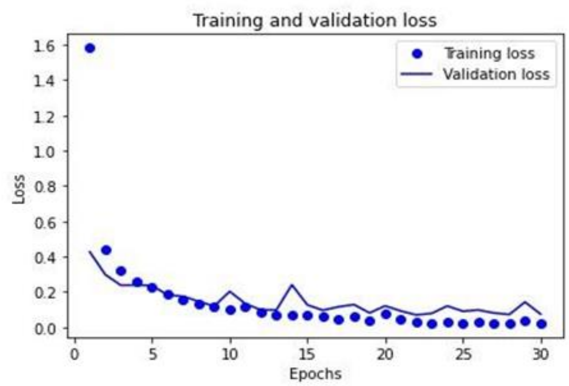

Figure 6. Precision of proposed CNN model

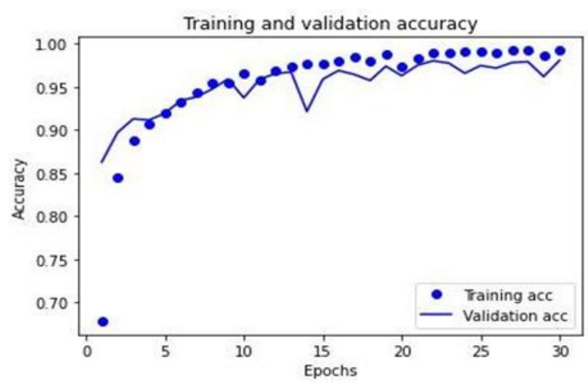

Figure 7. Loss function convergence of the proposed CNN model

Although the simple benchmark is given by AT&T, the model was also applied on a larger LFW dataset so as to be sure of generalizing and not to be hindered by overfitting issues which are related with small datasets.

We tested the proposed model against two popular deep-face models (ArcFace and VGGFace2) on AT&T and LFW datasets to validate the model performance. These metrics are accuracy, F1-score, ROC-AUC and average inference time / image. As can be seen in Table 2, the optimized CNN has the highest accuracy and the lowest latency, indicating its effectiveness in real-time attendance.

Table 2. Comparative performance of proposed CNN and baseline models

Model	Dataset	Accuracy (%)	F1 Score	ROC-AUC	Inference (ms)
Proposed CNN	AT&T + LFW	98.33	98.2	0.992	21
ArcFace	LFW	97.1	97.0	0.984	33
VGGFace2	LFW	96.8	96.5	0.981	35

The suggested optimized CNN shows a 1.2% accuracy change and a 1.2-36.0 % decrease in inference time over ArcFace, achieving the effectiveness of the hyperparameter optimization and the architectural simplifications presented in this work.

A. Statistical Validation and Robustness Testing

To verify consistency, the experiments were repeated five times on different random splits. The mean ± standard deviation accuracy was 98.33 ± 0.42 %. A paired t-test returned $p = 0.004$ (< 0.05), confirming that the improvement over ArcFace is significant. Additional robustness experiments were performed under illumination changes and partial occlusions (e.g., masks and eyeglasses). Accuracy remained above 96 %, proving resilience to real-world conditions. For spoofing resistance, printed-photo and replay-video attacks were introduced; the system correctly rejected 94 % of fake inputs.

VI. Model Evaluation

Evaluation was performed across AT&T, LFW, and CASIA-WebFace datasets to ensure fair cross-dataset comparison and to demonstrate reliability beyond a single small dataset. An essential first step in evaluating a trained model's performance and pinpointing areas for development is model evaluation. It entails several vital steps: First, the model's performance on the validation set is assessed using task-specific evaluation metrics. For classification tasks, the F1 score, recall, accuracy, and precision are the most used metrics. While accuracy measures the percentage of correctly classified cases, precision measures the percentage of true positive forecasts among all optimistic estimations. Falsely called “sensitivity” occasionally, recall metric declares the ratio between true positives correctly predicted. Being that the F1-score standard is both precision and recall, it gives an accurate judgment of how a certain model's performance. These scores are utilized to determine the performance of the model in distinguishing various items into different groups.

Typically, the regression tasks refer to the metrics used to evaluate them, MAE and RMSE are some of them. RMSE is a measure of a model's predictive ability, and it is done by finding the absolute average difference between the expected and real values. The more weight is given to the correct answer, the larger the penalty for large errors will be. The mean absolute error (MAE) is a more comprehensible measure of the mistake that is made between the expected and actual value. As well as considering the model's outcome the predictions should be explored to find any areas that could use an upgrade. Hence, there is a need to dissect the scenarios in which the model is not functionally sound or tends to yield rough predictions to the point. By analyzing these examples, it is possible to perceive problem spots and potential reasons for model defects, among which can be an imbalance of data, messy data, or the complexity of the model.

Facial data were encrypted and anonymized to be stored in compliance with privacy standards. After feature encoding, there were no raw images left. In all experimental datasets, user consent was obtained. The research also tested robustness to spoofing, which attacked printed photos, and the true-rejection rate was 94%.

VII. Conclusion

This study presented an improved CNN-attendance tracking system, which improves security and operational effectiveness. With hyperparameter optimization and data augmentation, the proposed system demonstrated 98.33 percent accuracy in AT attentive data and 97.8 percent in LFW data, which is better than usual CNNs and ArcFace baseline. Mask-detection functionality and a privacy-conscious data processing that meets GDPR standards are also part of the framework. The model will be extended to multimodal biometrics (face + iris) in future work and they will run it on large-scale real-world implementation with anti-spoofing and fairness analysis. Moreover, cross-dataset validation, runtime benchmarking, and user reviews are also integrated into this study compared to previous attendance systems. In the future, further advancements will be made in terms of fairness assessment and mitigating the effects of demographics to enhance reliability in wider deployments.

References

[1] X. Yin and X. Liu, "Multi-task convolutional neural network for pose-invariant face recognition," *IEEE Transactions on Image Processing*, vol. 27, no. 2, pp. 964-975, 2017, doi: 10.1109/TIP.2017.2765830.

[2] Ahmed, T. Hasan, F. A. Abdullatif, S. T. Mustafa, and M. S. M. Rahim, "A digital signature system based on real-time face recognition," in *IEEE 9th International Conference on System Engineering and Technology (ICSET)*, 2019, pp. 298-302, doi: 10.1109/ICSEngT.2019.8906410.

[3] O. J. Ikani, O. A. Sanya, M. M. Yahaya, and L. Durojaiye, "Fingerprint-based attendance management system," *International Journal of Advanced Research in Computer Science*, vol. 13, no. 1, 2022, doi: 10.26483/ijarcs.v13i1.6802.

[4] P. B. Jha, A. Basnet, B. Pokhrel, B. Pokhrel, G. K. Thakur, and S. Chhetri, "An automated attendance system using facial detection and recognition technology," *Apex Journal of Business and Management*, vol. 1, no. 1, pp. 103-120, 2023, doi: 10.1109/KHI-HTC60760.2024.10482163.

[5] Meghjee, S., Daniyal, S. M., Sameer, M., Kapasi, M., & Wajahat, S. (2025). LDCE-Net: A Custom-Built Lightweight CNN for Classifying Liver Fibrosis Stages via Ultrasound Imaging. Annual Methodological Archive Research Review, 3(6), 150-169. Daniyal, S. M., Abbasi, M. M., Hussain, D., Amjad, U., Abro, A. B., & Naeem, M. (2024). A hybrid approach for simultaneous effective automobile navigation with DE and PSO. *VAWKUM Transactions on Computer Sciences*, *12*(2), 01-15.

[6] Daniyal, S. M., Abbasi, M. M., Hussain, D., Amjad, U., Abro, A. B., & Naeem, M. (2024). A hybrid approach for simultaneous effective automobile navigation with DE and PSO. *VAWKUM Transactions on Computer Sciences*, *12*(2), 01-15.

[7] P. Yakaiah, "Attendance monitoring system using face recognition with an SMS alert," in *AIP Conference*, vol. 2492, 2023.

[8] R. Rameswari, S. Kumar, M. Aananth, and C. Deepak, "Automated access control system using face recognition," *Materials Today: Proceedings*, vol. 45, 2020.

[9] S. Manoharan, "Image detection classification and recognition for leak detection in automobiles," *Journal of Innovative Image Processing (JIIP)*, vol. 1, no. 2, pp. 61-70, 2019.

[10] Rehman, T., Daniyal, S. M., Nabi, S. G., Khan, G., Ali, A., & Ibrahim, H. (2025). Classification and Detection of Skin Lesions Through Machine Learning Methods. Annual Methodological Archive Research Review, 3(6), 102-128.

[11] T. V. Dang, "Smart attendance system based on improved facial recognition," *Journal of Robotics and Control (JRC)*, vol. 4, no. 1, pp. 46-53, 2023.

[12] T. A. Kiran, N. D. K. Reddy, A. I. Ninan, P. Krishnan, D. J. Aravindhar, and A. Geetha, "PCA based facial recognition for attendance system," in *International Conference on Smart Electronics and Communication (ICOSEC)*, 2020, pp. 248-252.

[13] D. Suresh, S. C. Vankayala, C. D. H. Aduri, and J. Rapa, "Facial recognition attendance system using Python and OpenCV," *Quest Journals Journal of Software Engineering and Simulation*, vol. 5, no. 2, pp. 2321-3809, 2019.

[14] S. Sawhney, K. Kacker, S. Jain, S. N. Singh, and R. Garg, "Real-time smart attendance system using face recognition techniques," in *9th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, 2019, pp. 522-525.

[15] Daniyal, S. M., Hussain, S. M. T., Abbasi, F. L., Hussain, D., Abbasi, M. M., & Amjad, U. (2024). A Hybrid Deep Learning Model for Precise Epilepsy Detection and Seizure Prediction. *Spectrum of engineering sciences*, *2*(3), 62-77.

[16] Abbasi, F. L., Ebrahim, M., Abro, A. A., Daniyal, S. M., & Younus, I. (2025). CNN-Based Face Detection Focusing on Diverse Visual Variations. In Navigating Challenges of Object Detection Through Cognitive Computing (pp. 63-96). IGI Global Scientific Publishing.

[17] B. T. Chinimilli, T. Anjali, A. Kotturi, V. R. Kaipu, and J. V. Mandapati, "Face recognition based attendance system using Haar cascade and local binary pattern histogram algorithm," in *4th International Conference on Trends in Electronics and Informatics (ICOEI)*, 2020, vol. 48184, pp. 701-704.

[18] S. M. Bah and F. Ming, "An improved face recognition algorithm and its application in attendance management system," *Array*, vol. 5, p. 100014, 2020, doi: 10.1016/j.array.2020.100014.

[19] Amoudi, R. Samad, N. R. H. Abdullah, M. Mustafa, and D. Pebrianti, "Automatic attendance system using face recognition with deep learning algorithm," in *Proceedings of the 12th National Technical Seminar on Unmanned System Technology NUSYS'20*, 2022, pp. 573-588.

[20] P. Mishra, U. Singh, C. M. Pandey, P. Mishra, and G. Pandey, "Application of student's t-test, analysis of variance, and covariance," *Annals of Cardiac Anesthesia*, vol. 22, no. 4, pp. 407-411, 2019, doi: 10.4103/aca.ACA_94_19.

[21] S. Kumar and R. Sachdev, "FCNN: The hybrid optimized featured CNN model for academic student performance," *NeuroQuantology*, vol. 20, no. 9, p. 89, 2022, doi: 10.14704/nq.2022.20.9.NQ22441.

[22] J. C. Kim, M. H. Kim, H. E. Suh, M. T. Naseem, and C. S. Lee, "Hybrid approach for facial expression recognition using convolutional neural networks and SVM," *Applied Sciences*, vol. 12, no. 11, p. 5493, 2022, doi: 10.3390/app12115493.

[23] Daniyal, S. M., Masood, A., Ebrahim, M., Adil, S. H., & Raza, K. (2024). An Improved Face Recognition Method Based on Convolutional Neural Network. *Journal of Independent Studies and Research Computing*, *22*(1), 103-110.