Optimizing Attendance System: Integrating Liveness Detection and Deep Learning for Reliable Face Recognition

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Abstract - The study focuses on using vitality detection and deep learning technologies in the context of facial recognition in an Information Technology (IT) presence management project. The combination of deep learning with vitality detection provides a considerable advancement in security and effectiveness. This work integrated vitality-detecting technology with in-depth learning in facial recognition systems. Vitality detection technologies are used to verify the authenticity of persons by examining live indicators such as movements or facial expressions before face recognition. Meanwhile, deep learning is used to analyze and process facial photos correctly by learning from large amounts of data and recognizing facial features in depth. The study data set consists of 1300 photographs of professional school instructors taken with official authority. Model testing and training are conducted in the Google Colab environment using Python and the Hardy package. The test findings showed an 87% accuracy in face recognition, proving the system's capacity to identify persons and distinguish real from false ones consistently. Furthermore, the performance of Liveness Detection achieves 92% accuracy, and the integration of Live Detection technology with Deep Learning at 78%.

Keywords: liveness detection, deep learning, face recognition, attendance management, integration technology

I. INTRODUCTION

The adoption of face recognition technology in attendance management has seen a growing prevalent trend across various industries [1]-[7]. However, one of the primary challenges in implementing this technology is security issues related to the potential for false attacks, such as using facial photos of vocational school teachers. Furthermore, great accuracy in face recognition is required to ensure that the system can correctly and effectively detect teachers' faces independent of position changes or lighting circumstances. According to a survey by Golasangi et al. [8], face recognition technology is reliable and efficient in recording employee attendance. Similarly, [1], [7], [9], and [10] affirm that face recognition technology is quite helpful in reducing queues during attendance, thus saving time and enabling employees to attend punctually. Although face recognition technology offers various benefits in attendance management, challenges and shortcomings still need to be addressed. According to Dang [11], face recognition technology has several limitations because it must be combined with other technologies for real-time use. Moreover, the responsiveness of face recognition technology to fluctuations in lighting, pose, and facial expressions is relatively weak, resulting in errors in individual recognition [3], [12], and [7], thus solutions need to be found to make the function of this technology more efficient. On the other hand, privacy and security aspects are also of particular concern, such as using sensitive data and data storage. Research by [1], [13] highlights the risks of using face recognition technology in the context of data privacy, especially concerning the use of biometric data accessible to unauthorized parties. Therefore, it is important to consider solutions to various challenges and implement appropriate data protection measures to ensure that the face recognition system is safe from threats and efficient. In this regard, one solution is the integration of liveness detection technology.

Liveness Detection technology emerges as an essential component in biometric security systems, particularly facial recognition applications. This technology differentiates between live human faces (real-time human faces) and photos/images. Alongside the continuous development of Artificial Intelligence and machine learning, these Live Detection algorithms are becoming increasingly sophisticated, capable of detecting subtle signs of life such as facial movements, blinking, and changes in skin texture [14]-[18]. Liveness detection has applications in various sectors, including attendance management systems, and classic security situations. Integrating Liveness detection technology with attendance systems improves the accuracy and dependability of employee attendance records, possibly reducing data breach threats. Additionally, the gathered data can be stored and protected with stricter and more advanced verification methods [19]-[22]. Thus, besides streamlining administrative processes, technology adoption can also strengthen accountability and transparency in workforce management practices, fostering a more efficient and secure work environment. This aligns with [19], [23], who states that implementing Liveness Detection technology provides a vital defense layer against fraudulent activities, enhancing the reliability and trust of biometric authentication systems across various sectors. However, to improve detection accuracy and precision, a combination with other advanced technologies is required [24]-[27]. For instance, deep learning is chosen as one common approach in this study.

Deep learning enables systems to learn from complex and varied data independently, thus enhancing the capability of Liveness Detection technology in recognizing subtle and sophisticated signs of life [28]-[30]. By harnessing the power of Deep Learning, Liveness Detection technology can continue to evolve and deliver more advanced and reliable biometric security solutions. This system can automatically learn facial attributes with high accuracy from enormous volumes of data using DNN architectures like CNN [31], [32]. Regarding attendance management systems, deep learning-based facial recognition technology is more efficient and accurate than older methods. Attendance systems that employ facial recognition minimize the need for physical interaction while also reducing the likelihood of errors or fraud that may occur with manual systems [33], [34]. According to [10], [35]-[38], CNN technology may be incorporated and taught to detect faces with high accuracy under a variety of situations, including poor light and position alterations. Implementing this technology in attendance systems enables real-time recording of employee attendance, hence improving data security and administrative ease [39], [40]. Thus, using deep learning in facial recognition systems for attendance enhances system accuracy while ensuring data integrity and speeding up overall administrative operations. Deep Learning can accurately analyze and process face photographs by learning from enormous volumes of data to detect facial traits in depth [41]-[46]. Meanwhile, Liveness Detection provides additional security by verifying that the studied object is a living subject rather than a photograph or video [22], [24], [47]. This is accomplished via techniques such as motion analysis, blink detection, and heat response measurement, which are difficult to replicate. These two technologies are particularly beneficial in security applications requiring user authentication and identity verification, such as access control systems or online transaction verification. Thus, integrating liveness detection with deep learning in face recognition has significant implications for designing more accurate and efficient attendance management systems. The proposed method in this study has several significant advantages that need to be clarified. First, integrating liveness detection technology with deep learning provides a high level of security in facial recognition systems. Second, the model's ability to distinguish between live subjects and fraudulent attempts enhances overall facial recognition accuracy. Third, fine-tuning techniques in deep learning models allow for adequate recognition of new faces not present in the initial training data. Thus, this research not only enhances the security of facial recognition systems but also improves accuracy and adaptability in attendance management.

II. METHOD

A. Dataset

This research utilizes a facial dataset of high-resolution images of vocational high school teachers in Indonesia. The dataset comprises data stored in a MySQL database, collected from the attendance systems based on face recognition from several partner vocational schools (SMK). The data was gathered randomly from various school attendance systems. It includes diverse information such as teacher personal identification, attendance photos, check-in times (absence), check-out times (absence), and tardiness information. However, in this study, the dataset used for liveness integration only utilizes photos and the face recognition system applied to the teachers' school attendance system. The collected data amounts to 998 entries with various attributes. The data underwent several preprocessing stages, including filling in missing data, removing duplicate data, and correcting errors. Feature selection was employed to choose the most essential and relevant features for research analysis. Finally, the data was transformed into CSV format with various features for research purposes. In this context, random sampling helps reduce bias in the dataset. Additionally, random data collection ensures that the sample data reflects various variations within the overall population. Therefore, random dataset sampling is crucial to ensure that the analysis and research results are more accurate, reliable, and applicable to a broader population. The image data used for training to testing includes images/photos with various pose variations, facial expressions, and diverse lighting conditions to reflect real-world conditions in the workplace. The quality of the data/samples in training and testing will determine the success of the research. In this case, all photos/images used as samples are uniformly converted to 224x224 pixels. The dataset follows the Pareto principle, with 80% of the dataset allocated for training purposes, leaving the remaining 20% for testing [48]. This principle illustrates a pattern where a small portion of input will result in most of the output in a system (Fig. 1). The images in row A are the original photos taken from the face recognition-based attendance system using live detection on attendance system based face recognition, which still retains various attributes including timestamp, teacher's name, attendance location, and time of attendance. On the other hand, the photo in row B is cropped, with the image size standardized and all its attributes removed for research purposes.

B. Training and Testing Model

The research environment was conducted using Google Colab with Python. In this case, the required libraries will be imported first (Keras and TensorFlow). The face recognition dataset was manually imported into the Google Colab session via the Python prompt on Google Colab. After the preparation is done, is loaded and preprocessed using the ImageDataGenerator module from Keras. Since the model used is VGG-16, all image sizes are adjusted to 224 x 224 pixels. For loading the VGG-16 model, the VGG16 function from the Keras library, which has already been trained, is used. Following that is modifying the pre-trained model's architecture by appending layers specifically trained for fine-tuning at the top. In training, the optimizer, loss function, and evaluation metrics are also set, while in model compilation, training is performed using a loop method (Fig. 2). After training is completed, the model's effectiveness is assessed using an independent dataset through the computation of evaluation metrics (in this research, accuracy is used).

In the model training phase, the tuning parameters used in this study are as follows:

- Optimizer: RMSprop. This optimizer is used to optimize the model training process by adjusting weights and biases so that the model can learn from the data more efficiently.
- Learning Rate: 2 x 10^{-5}. This learning rate will determine how quickly or slowly the model learns from the data. The correct value can affect the speed of the model's convergence.

Loss Function: Categorical Cross-Entropy. The loss function in this case is used to measure how well the model predicts the correct output. Categorical Cross-Entropy is suitable for multi-class classification problems.

Using a loop method, the model was trained for ten epochs on the training dataset (80% of the data), where each epoch involves the process of learning and adjusting the model's parameters. The performance of the model was then validated on the test dataset.

Fig. 1 Images of datasets

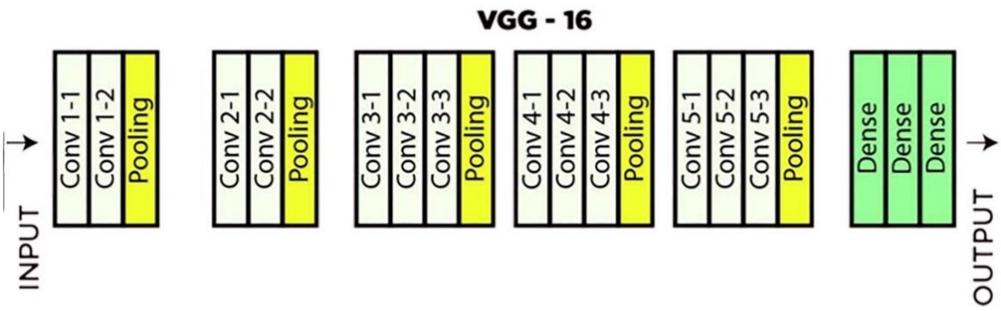

Fig. 2 The VGG-16 architecture used in the study

C. Integration of Liveness Detection Technology and Deep Learning for Face Recognition Attendance System

Liveness detection technology is implemented using a motion-based approach. The face recognition system for attendance utilizes high-quality cameras capable of capturing facial movements and expressions in detail. The motion detection algorithm runs in real-time to check for signs of life on the verified subject. Meanwhile, facial recognition employs a deep learning method grounded in CNN. The CNN model is trained before extracting features from facial samples. The research uses the VGG-16 architecture for the face recognition and proceeds with fine-tuning the model using datasets to improve recognition accuracy. The VGG-16 architecture used in this study can be seen in Fig. 2. The integration between liveness detection technology and deep learning is conducted in two stages. First, liveness detection technology is utilized to authenticate the subject's legitimacy before the facial recognition procedure begins. If the person is determined to be alive, the second stage is properly recognizing the face using the deep learning model. Combining these two technologies allows the system to ensure that only authentic faces are correctly identified. In contrast, false efforts such as pictures or video recordings may be efficiently detected and avoided.

Fig. 3 illustrates the architecture of the face recognition-based attendance system model developed using the integration of liveness detection techniques with deep learning (CNN). In this case, several steps differentiate it from conventional face recognition systems. In the authentication stage, there are preprocessing steps to establish the connection between the camera and CNN with liveness detection so that the camera opens and begins detecting faces. Once the camera captures a face figure, liveness detection and CNN automatically process the captured image to determine whether it depicts a human or not. If not, the camera captures the face again and re-verifies in the analysis step using liveness detection techniques. Next, if the captured face figure is detected as a living human, it matches the user's identity data (the respective teacher) with the system. If the data matches, attendance is accepted; otherwise, it is rejected, and the camera repeats the face capture process through the attendance camera. In the subsequent step after data acceptance, the attendance output appears as a timestamp record, similar to the bare face recognition-based attendance model in the system. In the next phase, the model will continue to be further developed and integrated with various other advanced technologies to enhance security and utilize data for predictive purposes and early security monitoring through anomaly detection and attendance pattern prediction.

III. RESULT AND DISCUSSION

In the model training phase, 80% of the dataset is loaded using the ImageDataGenerator module from Keras and then divided into batches for training and testing. Next, the pre-trained VGG16 model is loaded as the base part of the architecture, and additional layers are added on top for adjustment. The model is then compiled using the RMSprop optimizer with a learning rate of 2^{10-5} and a categorical cross-entropy loss function. The model is trained for ten epochs on the training dataset (80% of the data), and its performance is validated on the test dataset. After training the model on the prepared dataset, the model's performance is assessed using a separate testing dataset (20% of the dataset). This study uses relevant assessment criteria, particularly accuracy, to how effectively the investigated model recognizes actual faces. Utilizing the separate testing dataset, the resulting testing accuracy is 87%, suggesting that the trained model can properly detect faces when merging liveness detection technology and deep learning. In this case, for the specific parameter values and resulting performance metrics, refer to Table I, where the parameters used are Optimizer (RMSprop) with a Learning Rate of 2×10^{-5}, Loss function (Categorical Cross-Entropy), and Ten epochs. The model achieved an accuracy rate of 92% during training and 87% accuracy during model testing.

A. Performance Evaluation of Liveness Detection Technology

Accuracy, Precision, Recall, and F1-Score were used as assessment criteria. When measuring the performance of Liveness Detection Technology using established evaluation criteria, the higher the acquired values, the better the system's performance in differentiating real faces from false attacks. The assessment findings show that a liveness detection system can detect bogus assaults with high reliability. The performance results of liveness-detecting technique are shown in Table 1. With 95% precision, the motion detection algorithm distinguishes between real faces and phony photos. Furthermore, this system exhibits good skills in handling position changes, face emotions, and diverse lighting situations. Based on the accuracy, precision, and recall rates in Table I, the model testing results are promising and demonstratesolid performance in facial recognition using liveness detection technology and deep learning.

B. *Performance Evaluation of Deep Learning in Face Recognition*

Deep learning's effectiveness in facial recognition is evaluated using standard measures such as accuracy, precision, and recall. The deep learning model trained on the vocational high school teacher dataset demonstrated great recognition accuracy, with a value of 98% for detecting instructor faces. The model also has a high tolerance for position changes and illumination conditions. Furthermore, adding fine-tuning techniques to existing models significantly enhances performance notably in recognizing new faces not included in the initial training data. Table II displays how quantitative evaluation criteria such as accuracy, precision, and recall are stated numerically. Meanwhile, qualitative assessment metrics such as "Good" for posture and lighting tolerance, and "Improved" for fine-tuning the model, are kept in text form since they are difficult to quantify numerically.

TABLE I
THE RESULT OF PERFORMANCE EVALUATION METRICS VALUE ON TRAINING AND TESTING MODEL

Evaluation Metrics	Training Model	Testing Model
Accuracy	92%	87%
Precision	89%	85%
Recall	94%	90%

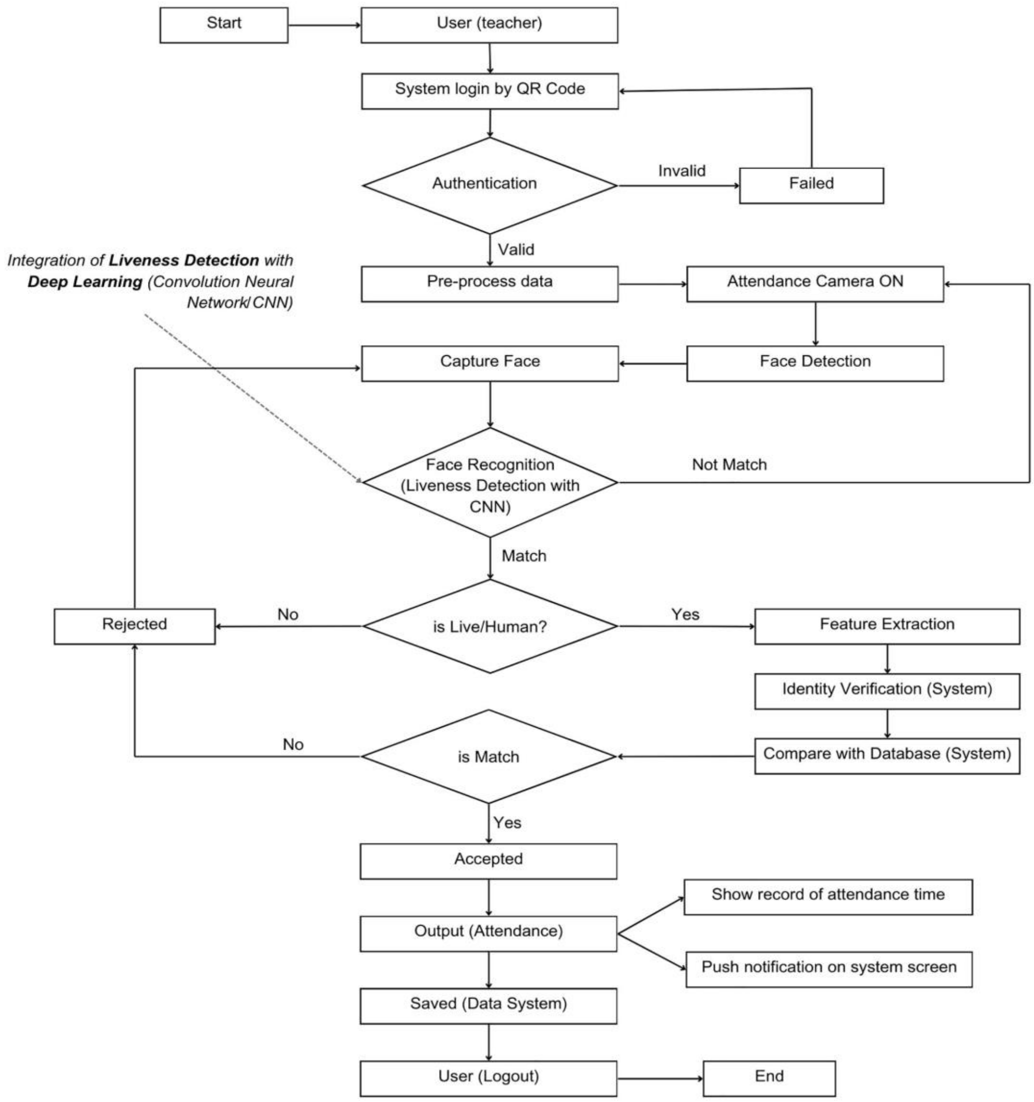

Fig. 3 Development of a face recognition-based attendance system model using the integration of liveness detection technology with deep learning (CNN) for accuracy and security of the attendance system

C. Analysis of the Integration Results of Liveness Detection Technology with Deep Learning in Face Recognition

The analysis of the results from integrating liveness detection technology with deep learning demonstrates a significant improvement in the security and accuracy of the face recognition system. By validating the authenticity of the subject before face recognition, the system successfully reduces the risk of fake attacks and identity misuse. This integration also helps enhance the overall performance of face recognition by ensuring that only actual faces present are identified. The analysis results indicate that this approach has great potential to be applied in various applications, including within systems (Table III). From these results, it is evident that the system Performs well in distinguishing between living subjects and fraudulent attempts, achieving an accuracy of over 98%. The system also tolerates environmental variations such as different lighting conditions and various facial poses. The fine-tuning technique applied to the deep learning models has also successfully improved recognition performance, especially in identifying new faces not present in the initial training data.

The research findings suggest that combining liveness detection technology with deep learning has the potential to improve the security and precision of facial recognition systems used in attendance management. Validating subjects' authenticity before the facial recognition process successfully minimizes the danger of phony assaults, such as those employing images or video recordings, which is consistent with [20], [22], [53]. Furthermore, applying intensely trained deep learning models considerably improves facial recognition accuracy. These findings indicate that this approach has great potential to enhance the efficiency and reliability of attendance management systems in vocational high schools. Moreover, there has been significant progress in developing face recognition systems of attendance management through the integration of liveness detection technology with deep learning, which aligns with previous research highlighting the added value of combining these two technologies. Previous research [41], [45], [46] has demonstrated that deep learning has a strong capability for detecting face characteristics in detail, while [22], [24] stresses the relevance of liveness detection in verifying subject authenticity. This technological integration improves the security of face recognition systems and increases accuracy, with a testing accuracy score of 87%, comparable with earlier research confirming the dependability of face recognition technology in documenting teacher attendance [8]. As a result, our research contributes significantly to building more dependable and adaptive systems for facial recognition-based attendance management.

TABLE II
PERFORMANCE EVALUATION OF DEEP LEARNING IN FACE RECOGNITION

Evaluation Metric	Value
Accuracy	0.98
Precision	0.95
Recall	0.96
Pose Tolerance	Good
Lighting Tolerance	Good
Fine-Tuning Model	Improve Performance

TABLE III
ANALYSIS OF THE INTEGRATION RESULTS OF LIVENESS DETECTION WITH DEEP LEARNING IN FACE RECOGNITION

No	Analyzed Outcome Variable	Analysis Decryption
1	Security Analysis ([49]	The use of liveness detection helps distinguish between live subjects and fraudulent attempts with an accuracy of over 92%. The trained model demonstrates the ability to detect fraudulent actions, such as the use of fake photos.
2	System Efficiency [50]	Integrating liveness detection with deep learning not only improves accuracy but also speeds up the system's response time. The application of this technology results in a more responsive and efficient face recognition system for attendance management.
3	Face recognition accuracy [51], [52]	After integration, the system achieved a face recognition accuracy rate of 87% in the testing phase. The model successfully recognized registered faces well, even in situations with varying poses and lighting conditions.

D. Implications for Attendance Management and Related Fields

The implications of this research for attendance management are increased security and accuracy in recording the attendance of vocational high school teachers' faces. With liveness detection and deep learning technology, institutions can ensure that their attendance data is more reliable and accurate. Additionally, this technology's application can have positive impacts in related fields such as physical security management, access management, and information security. Based on the research findings, that resources be continued to invest in developing liveness detection and deep learning technology for attendance management in both school and broader institutional settings.

IV. CONCLUSION

From this research, the integration of liveness detection technology with deep learning in facial recognition has significantly contributed to enhancing the security and accuracy of attendance management systems. The models trained in this study achieved a testing accuracy rate of 87%, demonstrating proficiency in facial recognition by incorporating liveness detection and deep learning technologies. Moreover, the system successfully distinguished between live subjects and fraudulent attempts with an accuracy of over 92%, highlighting its capability to address security challenges in facial recognition. Therefore, integrating liveness detection technology with deep learning improves security and accuracy in attendance management systems. The research also demonstrated that the deep learning models trained using 20% of the dataset achieved a high recognition accuracy rate, reaching 98% in identifying teachers' faces. Additionally, these models showed good tolerance to pose variations and lighting conditions, indicating robust adaptability in facial recognition. Thus, this study Significantly contribute to building more reliable and adaptive facial recognition-based attendance management systems. By validating the authenticity of subjects before facial recognition, the system effectively reduces the risk of false attacks and identity misuse, thereby enhancing security and accuracy in attendance management. Lastly, this research opens the door for further development in liveness detection technology and deep learning for attendance management applications. Several areas can still, including the development of more advanced and adaptive liveness detection algorithms. Additionally, integration with other biometric technologies such as voice or fingerprint recognition can be explored. Moreover, data security and privacy can be further enhanced using combinations of other technologies such as machine learning. Future research can also explore the application of this technology on a larger scale, including in more complex work environments or different industrial contexts.

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