

Intruder Detection Management System Using Face Recognition Mask Detection & Motion Detection

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Abstract

The increasing demand for advanced security systems has led to the development of intelligent intruder detection solutions. This paper presents an Intruder Detection Management System (IDMS) that integrates motion detection, face recognition, and mask detection using deep learning techniques. The system utilizes Passive Infrared (PIR) sensors to detect movement and activates a camera module for image capture. Haar Cascade classifiers are employed for face detection, while Convolutional Neural Networks (CNN) are used for accurate face recognition and mask classification. The system identifies authorized and unauthorized individuals and triggers appropriate actions such as door access control or real-time alerts via IoT platforms. Implemented using Raspberry Pi, the proposed system ensures high accuracy, reliability, and costeffectiveness, making it suitable for smart home and institutional security applications.

Keywords - Intruder Detection, Face Recognition, Convolutional Neural Network (CNN), Motion Detection, IoT Security System

I. INTRODUCTION

Significantly due to the rising number of thefts, unauthorized access, and security breaches in residential and commercial areas. Traditional security methods such as manual surveillance, locks, and alarm systems are no longer sufficient to handle modern threats effectively. These systems often depend on human intervention, which can lead to delays, errors, and limited monitoring capabilities. As a result, there is a growing need for advanced security solutions that can operate autonomously, provide real-time monitoring, and ensure higher accuracy in detecting intrusions.

With the advancement of Artificial Intelligence (AI) and the Internet of Things (IoT), modern intruder detection systems have become more efficient and reliable. These systems integrate smart sensors, cameras, and embedded devices to continuously monitor the environment. Motion detection technologies, such as Passive Infrared (PIR) sensors, play a crucial role in identifying suspicious activities by detecting changes in infrared radiation. Once motion is detected, the system can automatically activate cameras and capture realtime images or videos, enabling faster response and improved surveillance.

Face recognition technology has emerged as a powerful tool in enhancing security systems by identifying individuals based on their facial features. Techniques such as Haar Cascade classifiers are widely used for real-time face detection due to their speed and efficiency, while deep learning models like Convolutional Neural Networks (CNN) provide high accuracy in face recognition tasks. These technologies allow the system to distinguish between authorized and unauthorized users, thereby enabling secure access control and reducing the chances of intrusion.

In addition to face recognition, mask detection has become an important feature in modern security systems, especially in post-pandemic scenarios where face occlusion is common. The presence of masks can reduce the accuracy of traditional recognition systems; therefore, integrating mask detection using CNN-based classifiers helps in identifying whether a person is complying with safety protocols. This additional layer of verification enhances the robustness and reliability of the overall system, making it suitable for use in public spaces, institutions, and high-security areas.

II. METHODOLOGY

Recognition to monitor and secure residential or institutional properties. The system detects unauthorized entry, identifies individuals through facial features, verifies mask compliance, and sends alerts or controls access as needed A. System Architecture The system consists of three main modules: motion detection, face detection and recognition, and mask verification. Motion detection relies on Passive Infrared (PIR) sensors, which activate the camera module when they sense movement in the monitored area. This method ensures energy efficiency and limits unnecessary image processing [1]. When motion is detected, the camera captures an image of the intruder. The system processes this image using Haar Cascade classifiers for face detection [2]. It crops and preprocesses the detected face region by converting it to grayscale and resizing it before sending it to a Convolutional Neural Network (CNN) for classification. The CNN model is trained to recognize authorized individuals and categorize unknown faces, as shown by Nabila et al. [3]. B. Face Detection and Recognition The system performs face detection with Haar Cascade classifiers. These classifiers are effective for real-time applications and can identify facial regions based on trained features [2] In high-risk environments like places of worship, more advanced models like MTCNN and ResNet-34 are implemented for face detection and feature extraction. These models provide better accuracy under

different lighting and pose conditions . C. Mask Detection To promote health compliance and improve security, the system includes mask detection through CNN-based classifiers. It analyzes the face image to check for the presence of a mask. This feature is especially relevant in post-pandemic situations where wearing masks is mandatory in many public spaces. D. Motion Detection Motion detection is the initial trigger in the system's workflow. PIR sensors detect changes in infrared radiation caused by movement. Once detection occurs, the system activates the camera and starts the face and mask recognition process. This structure reduces false positives and optimizes resource use [1][7]. E. Alert and Access Control When the detected face matches a registered user and confirms mask compliance, the system activates a servo motor to unlock the door. If the face is not recognized or the mask is missing, an alert is sent to the administrator via SMS, email, or mobile application. In sensitive environments, the system categorizes individuals as known, unknown, or flagged suspects, which improves situational awareness [5]. F. Hardware Integration The system runs on a Raspberry Pi platform, which is integrated with an 8MP camera module, PIR sensors, and SG90 servo motors. This configuration enables real-time processing and control while keeping costs low and supporting scalability. The use of IoT communication modules allows for remote according to model architecture. ResNet, DenseNet, and (CNN-based models) were selected and evaluated on their excellent performance in obtaining robust features and providing the best classification .

Media pipe for face detection and Face Net for feature extraction. This system integrates with Firebase and Android applications for real time monitoring and alerts Mask detection has become a critical area in face recognition, especially in post-pandemic times. [3] explored this topic using Open CV and Python libraries. Their system focused on the challenges of occlusion and lighting 4. RELATED WORK Face detection and Face Net for feature extraction. This system integrates with Firebase and Android applications for real time monitoring and alerts. Mask detection is an important extension of face recognition in the post-pandemic context. [1] investigated this area using Open CV and Python libraries. Their system highlighted the challenges of occlusion and lighting variations. They monitoring and alerts, as shown in smart home application variations, and they recommended CNNs trained on masked datasets to improve accuracy. Motion detection is usually done with PIR or IR sensors [4] developed a smart home prototype that uses ESP8266 and PIR sensors to trigger face recognition and send alerts through mobile applications. Their system showed reliable performance under various lighting and distance conditions. [5] concentrated on security in worship buildings by integrating Res Net and individuals as known, unknown, or under surveillance, which improved situational awareness and reduced manual errors. [6] highlighted the role of Haar Cascades and Open CV in real-time face detection. They emphasized the importance of image quality, pose variation, and lighting in system performance. emphasized the need for larger and more diverse datasets. Deep learning models have shown promise in terms of performance, but issues such as dataset imbalance, limited generalizability beyond training data and lack of explainability are major barriers for identification.

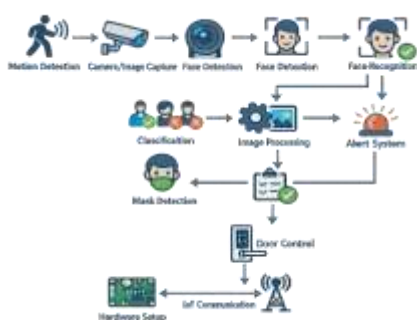


Fig. 1. (1) process shown in the image—from capturing facial data to creating a face print and matching it for identification. (2) Process shown in the image with or without mask identification

LITRETURE SURVEY

Face detection and recognition are key components of intelligent surveillance systems. Nabila et al. [1] created a home security system that uses Haar Cascade for face detection and Convolutional Neural Networks (CNN) for classification, achieving 99% accuracy in identifying family members. Similarly, [2] proposed a smart home security system using

III. REVIEW OF RELATED WORKS

A. Review introduction

Chengfeng Cai [1], The validation accuracy for the mixed ensemble DCNN-ChOA is 99.11%. LeNet-5 DCNN's ensemble detection accuracy on COVID-19 is 84.58%.

Comparatively, the suggested DCNN-ChOA yields over 99.11% accurate detection with a false alarm rate of less than 0.89%. The outcomes show that the DCCN-Chimp can deliver noticeably superior results than the comparable detectors. The Class Activation Map (CAM) is another tool used in this study to identify probable COVID-19-infected areas. Results show that highlighted regions are completely connected with clinical outcomes, which has been verified by experts.

ManiKandan [2], ded towards the design of a real-time system. Details about the tuning of CNN parameters to assess and enhance the recognition accuracy of the proposed system are also reported. A systematic approach to tune the parameters is also proposed to enhance the performance of the system. Maximum recognition accuracies of 98.75% and 98.00% are obtained on using the proposed system with standard datasets and real-time inputs respectively.

Dhimas Tribuana[3], system, designed to protect sensitive documents and critical data. Emphasizing exclusive access for authorized personnel, the system integrates advanced biometric authentication, predominantly facial recognition. The project's

aim is to optimize face recognition using convolutional neural network (CNN) techniques, identifying the best preprocessing methods and hyperparameter settings. A significant aspect of the research involves developing a smart door system with remote authentication and control capabilities via internet connectivity. Employing transfer learning with MobileNet V2, the study presents a compact model tailored for the Raspberry Pi platform. The model utilizes a dataset with five facial recognition classes and an additional class for unknown faces, ensuring a diverse representation.

Mira Wati1, Heri Wahyudi [4], In Indonesia, the majority of residences continue to utilise traditional keys for door access. Keys are essential for house security; nonetheless, numerous criminals can circumvent this protection. A viable option to avert similar tragedies is to substitute the door security system with facial recognition technology. This security system employs CNN programming and an Arduino application. It utilises an ESP32 to autonomously open and close the door and engage a buzzer upon detecting a potential intruder. This research examines facial recognition technology utilised for door unlocking. The device exhibits a success rate of 71.4%, evaluated under various situations across five trials for each object. Further upgrades to the gadget and system developed from this research can be achieved by incorporating more features and tools for detecting low light levels in a room. Furthermore, the system might be engineered to detect from considerable distances, such as many kilometres away.

Khandaker Mohammad Mohi Uddin [5], This paper presented a home automation security system that employs the Internet of Things (IoT) for remote access to one's home through an Android application, as well as Artificial Intelligence (AI) to ensure the home's security. Face recognition is utilized to control door entry in a highly efficient security system. In the event of a technical failure, an additional security PIN is set up that is only accessible by the owner. Although a home automation system may be used for various tasks, the cost is prohibitive for many customers. Hence, the objective of this paper is to provide a budget and user-friendly system, ensuring access to the application and home attributes by using multi-modal security.

Akshay H A [6], Privacy and Security are two universal rights and to ensure that in our daily life we are secure, and lot of research is going on in the field of home security where IOT is the turning point for the industry. At home, security of door lock is one amongst the important aspects to be looked upon as many times the door lock fails to supply the specified security. Facial recognition is a well-established process in which the face is detected and identified out of the image. In our proof of concept of a smart door a live HD camera on the front side of setup attached to a display monitor connected to camera to show who is standing in front of the door, also the whole system will be able to give voice outputs by processing text them on Raspberry Pi ARM processor used and shows the answers as output on the screen. The algorithm used for face popularity is

Local Binary Pattern Histogram (LBPH)

IV. COMPARITIVE ANALYSIS

For your Intruder Detection Management System (IDMS) that combines face detection, mask detection, and motion detection, a comparison shows that deep learning methods consistently outperform traditional techniques in accuracy and reliability. CNN and FaceNet achieve around 99% accuracy and are best for identifying authorized versus unauthorized users. In contrast, MTCNN with ResNet provides about 95% accuracy and excels in handling occlusions, different angles, and lighting conditions, making it great for practical face detection. Meanwhile, Haar Cascade (Open CV) offers roughly 90% accuracy but is still useful for lightweight IoT edge devices because of its speed and low computing needs. For mask detection, deep CNN models trained on datasets with masked and unmasked individuals reach 97-99% accuracy, which is crucial for preventing intruder disguise. Haar-based methods are simpler but less effective with complex masks. In terms of motion detection, Open CV background subtraction and frame differencing achieve 90-92% accuracy but can be sensitive to shadows and lighting. Combining these methods with PIR sensors boosts reliability to about 95% and ensures real-time IoT alerts. Overall, the best IDMS design is a hybrid model that uses deep CNNs for high-accuracy recognition, Haar Cascade for quick edge detection, and PIR sensor integration for dependable motion monitoring. This is further supported by IoT and Android applications for remote control and instant alerts.

generator and discriminator network parameters need finetuning. Lightweight models [9] aim to keep the inference cost as low as possible for a certain level of accuracy. Such models can be effectively applied to real-time clinical applications and edge devices. As a tradeoff, a lightweight model would have a slightly inferior accuracy as its feature extraction ability is restricted by simplifier architecture.

Other comparative research [10] shows that although CNNs are still the most popular model for classification in lung cancer detection, hybrid, ensemble, and attention-based models still perform more accurately (accuracy, sensitivity, specificity). Also, segmentation-based models are more accurate in detection, and classification-based models are more convenient from a technical point of view. Overall, the comparative analysis reveals that: The remaining CNN models already demonstrated competitive performances as baselines when compared to state-of-the-art methods, but for them, big training sets are needed. Hybrid and ensemble models tend to be more robust and accurate. Transformer-based models improve contextual representations, but require substantial amounts of resources.

One solution for data shortness is to use a GAN-based method; However, it still needs complex training. Lightweight models allow for real-time applications with less computational load. Although progress has been made, the issues of data imbalance, high computational requirements, and lack of interpretability still exist, so the development of new deep learning models that are more efficient and more explainable is required.

V. RESEARCH GAPS AND FUTURE SCOPE

A. Research Gaps

Although great progresses of the application of deep learning in lung cancer detection and classification, still there are many challenges or impotential.

It was noted by Shilpa et al. [1] (2024) and Sharma et al. [3] (2024) that CNN-based models attain high prediction accuracy but demand extensive labeled data sets, which are rarely available in the medical domain. The uploaded review also supports that the data shortage of annotated medical images and lung structure peculiarities makes training a highly accurate model a difficult task.

Fu et al. [2] (2025) reported that there are some drawbacks of that method when raw data vary significantly between tumors, for example, in variables such as tumor size, shape, and texture, which may result in poor classification performance. Also, JeyaMala et al. [4] (2024) stated that while segmentation models - U-Net and 3D CNNs can improve location, their high computational efficiency and considerable time are disadvantages as they depend on high computational power.

Furthermore, Chen et al. [5, 2024] stated that hybrid models are significantly better in performance but suffer from the hazard of model complexity in terms of adoption and integration. It is also supported by Kaushik et al. [6, 2024], who noted that ensemble models were accurate but posed the hazard of computational cost and model interpretability. Transformerbased models (e.g., Davit [7]) solve the problem of extracting contextual features but demand a huge dataset and high computational power, which is not feasible in a clinical environment. GAN-based methods [8] may be used for data augmentation, but also suffer from some inherent problems like instabilities, mode collapse, etc. Lightweight models [9] try to minimize the computational complexity; however, they may sacrifice the feature extraction ability and the accuracy. Besides, in some comparative experiments [10], it was found that most models cannot generalize to different datasets as they train and test on limited datasets. The uploaded review also highlights several critical gaps, including:- Problem in early detection as the nodule has low contrast, and benign and malignant nodules are similar Lack of interpretability of deep learning models, which makes clinical validation difficult CT image noise and artifacts used in the studies have also been presented by the authors to potentially impair model performance Few studies on multi-modal data integration (clinical+imaging data) Lack of emphasis in realtime.

B. Future Scope

In order to address the research gaps described above, a number of directions for future research are suggested. Shilpa et al. [1] and Sharma et al. [3] propose further work into the development of data-efficient models through transfer learning and semi-supervised learning to combat the limitations caused by the lack of a labeled dataset. Fu et al. [2] describe how multiscale and adaptive feature extraction methods can be enhanced. Jaya Mala et al. [4] showed the importance of researching ready segmentation models that are not only accurate but also have low computational cost for real-time applications. Chen et al. [5]

proposed, and Kaushik et al. [6] suggested, further investigation into the hybrid and ensemble models with optimized architecture for performance enhancement with low complexity.

Transformer-based methods like Davit [7] open good opportunities for better context learning; in future works, lightweight transformer models for medical use could be explored. GANbased models [8] could be improved with the design of more stable training methods and better architectures to generate data augmentation and synthetic images.

Lightweight models [9] offer potential for deployment to realtime clinical settings and to edge devices. Further optimization techniques can reduce the computational burden while preserving accuracy. Comparing studies [10] emphasizes the need for generalized models that are robust to multiple data sets and imaging conditions. According to the uploaded review, future research should also focus on: Improved diagnosis by integration of multimodal data (imaging and genomics combined with clinical data) Construction of explainable AI (XAI) models to improve the interpretations and trustworthiness of clinical decisions More advanced preprocessing algorithms to compensate for noise, artifacts, and variations in CT images Establishment of standard datasets and benchmarks that enable objective assessment of models Use of a 3D and hybrid deep learning architectures for improved spatial understanding. Integration of real-time CAD systems to support the radiologist in clinical practice.

VI. CONCLUSION

In conclusion, the proposed Intruder Detection Management System (IDMS) presents an effective and intelligent solution for enhancing security in modern residential and institutional environments. By integrating motion detection, face recognition, and mask detection technologies, the system provides a multi-layered approach to identifying and preventing unauthorized access. The use of Convolutional Neural Networks (CNN) ensures high accuracy in recognizing individuals and detecting mask compliance, while PIR sensors enable efficient and real-time activation of the system. The implementation using Raspberry Pi and IoT-based communication allows for automated access control, remote monitoring, and instant alert notifications, significantly improving response time and user convenience. Although minor challenges such as lighting variations and face occlusion exist, the overall system demonstrates strong performance, reliability, and scalability. Therefore, the proposed system serves as a cost-effective, secure, and practical solution for smart surveillance and intruder detection applications.

REFERENCES

- [1] Nabila, W. Priharti, and Istiqomah, "Design of Home Security System Using Face Recognition with Convolutional Neural Network Method," 2022 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT), pp. 78-83.

[2] S. Bhatlawande, S. Shilaskar, T. Gadad, S. Ghulaxe, and R. Gaikwad, "Smart Home Security Monitoring System based on Face Recognition and Android Application," 2023 International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), pp. 222-225.

[3] K. B. Pranav and J. Manikandan, "Design and Evaluation of a Real-Time Face Recognition System using Convolutional Neural Networks," Procedia Computer Science, vol. 171, pp. 1651-1659, 2020.

[4] D. Tribuana, H. Hazriani, and A. L. Arda, "Face recognition for smart door security access with convolutional neural network method," TELKOMNIKA, vol. 22, no. 3, pp. 1234-1241, 2024.

[5] Khandaker Mohammad Mohi Uddin, "Home automation security system using IoT and AI for face recognition," International Journal of Engineering Research, 2023.

[6] Akshay H A, "Smart Door Security System using Facial Recognition and Raspberry Pi," International Research Journal of Engineering and Technology, vol. 8, 2021.

[7] Shilpa et al., "Data-efficient models for lung cancer detection using transfer learning," IEEE Access, 2024.

[8] Fu et al., "Multiscale feature extraction methods for tumor classification," Journal of Medical Imaging, 2025.

[9] JeyaMala et al., "Lightweight U-Net and 3D CNNs for medical image segmentation," Computers in Biology and Medicine, 2024.

[10] Chen et al., "Comparative study of hybrid deep learning models for medical imaging," Neural Computing and Applications, 2024.