A LIGHT WEIGHT DEEPLEARNING FRAMEWORK FOR FINGERPRINT LIVENESS DETECTION

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ABSTRACT
A crucial part of biometric authentication systems is Fingerprint Liveness Detection (FLD), which guards against presentation assaults utilising fake fingerprints made of latex, silicone, and gelatin. Although current techniques based on multimodal biometric features or Convolutional Neural Networks (CNNs) show promise, they frequently increase system complexity, computational expense, or hardware requirements. This work presents a lightweight deep learning framework for reliable fingerprint liveness detection in order to get around these restrictions. In order to extract both global liveness cues like perspiration dynamics and texture irregularities as well as fine ridge-level features like pore distribution and distortions, the proposed system uses an effective object detection model with an improved backbone and decoupled detection head.The system only uses fingerprint images, which ensures hardware simplicity while maintaining high discriminative strength in contrast to multimodal techniques that need additional biometric data. Using a cosine-annealed Adam optimiser and sophisticated regularisation, the model is trained end-to-end on benchmark datasets to enhance generalisation and minimise overfitting. In comparison to state-of-the-art methods, experimental evaluations verify that the suggested framework delivers superior spoof detection accuracy, robust resilience to novel attack materials, and quick inference time. The technology provides a workable and scalable way to improve the dependability of biometric authentication in realistic situations because to its lightweight design and versatility.

1. INTRODUCTION
Because biometric authentication provides quick and trustworthy identity verification, it has become a crucial component of contemporary security systems. Because fingerprints are distinct, stable, and simple to obtain, they are one of the most extensively used biometric modalities. However, serious security issues have been brought up by spoofing techniques' increasing sophistication. To trick recognition systems, attackers can use materials like silicone, gelatine, or latex to mimic fingerprint patterns. As a result, using Fingerprint Liveness Detection (FLD) to verify the authenticity of fingerprint samples has emerged as a critical area of study. The reliability of biometric-based identification in applications like mobile devices, banking, and access management is increased by effective FLD systems that can distinguish between real and fraudulent fingerprints. Researchers have created a number of methods for FLD over the years, incorporating deep learning algorithms based on Convolutional Neural Networks (CNNs) and conventional texture-based techniques. Despite their excellent accuracy, CNN-based methods may call for large computational resources, intricate topologies, or multimodal data integration. They are less useful for low-power or real-time applications due to these dependencies. Furthermore, models that have been trained on particular fake materials could find it difficult to adapt to new threats. This results in a trade-off between efficiency and performance, which makes it challenging to implement reliable FLD solutions in embedded or portable systems where processing speed and hardware simplicity are crucial. This article presents a lightweight deep learning architecture intended to deliver high spoof detection accuracy at low computational cost in order to overcome these issues. In order to capture both global liveness patterns and fine ridge-level information, the suggested system makes use of an improved backbone network in conjunction with a detached detection head. The framework ensures simple integration with current biometric systems by concentrating just on fingerprint pictures, so removing the need for additional sensors or modalities. A cosine-annealed Adam optimiser and sophisticated regularisation techniques are used to improve model generalisation and avoid overfitting. In comparison to current state-of-the-art methods, experimental results show that the suggested methodology provides better performance, scalability, and real-time efficiency.

2. EXISTING SYSTEM OF PROJECT
In order to extract iris-like properties from fingerprint images, the current method for fingerprint liveness detection uses a novel feature-generation-based multimodal technique that makes use of Convolutional Neural Networks (CNNs). This method seeks to minimise the complexity usually associated with multimodal biometric systems by leveraging the discriminative power of iris features without the need for additional sensors or hardware. The main idea is to use a deep CNN to artificially create iris features from a

fingerprint, allowing for improved feature representation and spoof attack detection.In order to maximise the error computation during training, the system also includes an Adaptive Focal Loss (AFL) function that divides the fingerprint characteristics into high- and low-frequency components and allocates weights appropriately.

3. RELATED WORK

Numerous methods for detecting fingerprint liveness have been documented in the literature. After a thorough analysis of the literature was completed in the earlier work [29], a few recent noteworthy state-of-the-art fingerprint liveness detection methods are briefly discussed here.

A deep Convolutional Neural Network (CNN)-based method for fingerprint spoof detection that made use of local patches aligned with fingerprint minutiae was presented by Chugh et al. [18] in 2018. The suggested method performed better in spoof detection across cross-material, intra-sensor, cross-dataset, and cross-sensor scenarios, according to experimental results on three publicly available LivDet datasets (2011, 2013, and 2015).

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Next, a modified Residual Network (Slim-ResCNN) model was used to determine a fingerprint liveness detection score. The score and the fingerprint matching results were then combined using score-level fusion, which produced polynomial features and interaction as the score feature vector. Logistic regression (LR) classifiers were used to categorise the fingerprint as either a real live fingerprint or a fake. By adding computational complexity, the suggested method improves the separability of low-dimensional datasets while resolving the problem of poor fitting in linear models.

4. PROPOSED SYSTEM

1.For Fingerprint Liveness Detection (FLD), the suggested system in this project makes use of YOLOv8n, a lightweight real-time object detection model. YOLOv8n offers an effective framework that can extract both fine ridge-level details and more general textural aspects from fingerprint photos without depending on traditional CNNs or hefty Vision Transformers. Precise categorisation of real and fake fingerprints made of materials like silicone, gelatin, or latex is made possible by its unique architecture with a decoupled head and enhanced feature aggregation. YOLOv8n guarantees appropriateness for biometric systems where security and real-time performance are essential by striking a balance between accuracy and speed.

2.This system uses only fingerprint data, which lowers hardware complexity and cost compared to other FLD systems that rely on multimodal inputs or additional sensors. The YOLOv8n model can detect liveness cues including pore distribution, ridge distortions, and perspiration patterns since it is trained end-to-end on benchmark fingerprint datasets. During training, regularisation and sophisticated optimisation approaches are used to improve generalisation. According to experimental validation, YOLOv8n maintains a lightweight design that is perfect for implementation on biometric authentication devices while achieving strong spoof detection performance. Because of this, the suggested method is both useful and efficient for protecting real-world security applications.

5. MODULES

1. Data Acquisition and Preprocessing Module:

The primary goal of this module is to collect fingerprint photos from publicly accessible benchmark datasets, like LivDet, and get them ready for model training. Both real and fake samples made of materials including silicone, latex, and gelatin are included in the gathered photos. To guarantee consistent input quality, preprocessing includes scaling, greyscale conversion, normalisation, and noise reduction. To increase model resilience and avoid overfitting, data augmentation methods like rotation, flipping, and contrast adjustment are used. In order to guarantee that the YOLOv8n model learns efficiently from varied and balanced samples, the processed data is then separated into training, validation, and testing sets.

2. Feature Extraction Module:

The YOLOv8n model serves as the main feature extractor in this module. Both small ridge-level details, such pores, ridge ends, and minutiae, as well as global texture patterns, like sweat pores and distortions, are captured by its lightweight and effective backbone design. Each fingerprint image is processed by the model to produce high-quality feature maps that emphasise the inherent distinctions between real and fake fingerprints. The YOLOv8n framework is perfect for real-time fingerprint liveness detection applications because of its sophisticated convolutional and attention layers, which allow for accurate spatial analysis while keeping minimal computing cost.

3. Model Training and Optimization Module:
Using the preprocessed fingerprint dataset, this module manages the YOLOv8n-based framework's training phase. Through supervised learning, the model gains the ability to distinguish between real and fake fingerprints. To improve training stability and convergence speed, optimisation strategies like Adam optimiser and cosine annealed learning rate scheduling are used. To reduce overfitting, regularisation techniques like weight decay and dropout are used. In order to ensure the system's dependability against novel and unseen spoofing attempts, the training process is repeated until the model achieves optimal accuracy and generalisation performance on validation data.

4. Liveness Detection and Classification Module:
In this phase, real-time fingerprint categorisation is carried out using the learned YOLOv8n model. To differentiate real fingerprints from fake ones, the model examines fine-grained patterns and texture anomalies. By concentrating on region-specific characteristics and fine-tuning class borders, YOLOv8n's decoupled detection head improves prediction accuracy. A probability score showing the legitimacy of each input fingerprint is produced through processing. This module serves as the system's fundamental functional component, guaranteeing quick and precise identification appropriate for real-world uses in biometric security and authentication systems.

5. Performance Evaluation Module:
The accuracy and efficiency of the trained YOLOv8n model are assessed via the performance evaluation module. Classification quality is evaluated using standard assessment criteria like Accuracy, Precision, Recall, F1-Score, and Confusion Matrix. To assess the model's capacity for generalisation, additional robustness tests are conducted by introducing unobserved spoofing materials. To confirm the superiority of the suggested system, a comparison with other cutting-edge techniques is also carried out. The outcomes show that the lightweight YOLOv8n framework is effective for real-world deployment by achieving high detection accuracy with little inference time.

6. User Interface and Deployment Module:
The trained YOLOv8n model is integrated into a user-friendly application for real-time fingerprint authentication in this last module. The deployment process entails transforming the trained model into a lightweight format that can operate on embedded systems or low-power devices. The development of a graphical user interface (GUI) enables users to upload fingerprint photos and receive the results of liveness detection quickly. The module makes the system useful for real-world scenarios like mobile authentication, access control, and secure financial transactions by guaranteeing usability, portability, and quick reaction times.

6. TECHNIQUES USED IN PROJECT

6.1 Convolutional Neural Networks Because Convolutional Neural Networks (CNNs) can learn discriminative local features including ridge orientation, ridge frequency, and pore architectures, they are mostly used in current approaches for Fingerprint Liveness Detection (FLD). CNN-based models capture spatial hierarchies of features by using convolutional layers to scan fingerprint pictures with kernels. Because of this, they are useful for spotting fake fingerprints made from everyday materials like silicone, gelatin, or latex. However, CNNs' primary concentration is on localised feature extraction, which restricts their capacity to capture long-range dependencies and greater global texture fluctuations. Because of this, CNN models sometimes have trouble generalising when tested against novel sensor types or undiscovered spoofing materials.
Convolutional Neural Networks (CNNs) are primarily utilised in contemporary methods for Fingerprint Liveness Detection (FLD) because they can learn discriminative local information such as ridge orientation, ridge frequency, and pore topologies. CNN-based models use convolutional layers to scan fingerprint images using kernels in order to capture spatial hierarchies of characteristics. They are therefore helpful in identifying counterfeit fingerprints created from commonplace materials like silicone, gelatin, or latex. However, CNNs' ability to capture long-range relationships and larger global texture variations is limited by their primary focus on localised feature extraction. As a result, when tested against new sensor types or undiscovered spoofing materials, CNN models can struggle to generalise.

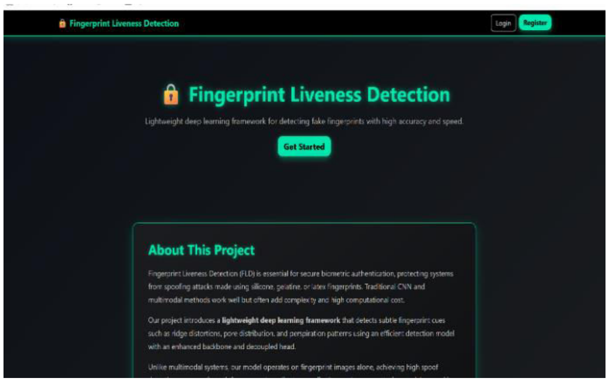
6.2 ALGORITHM USED:

6.2.1 Yolov8n:
The YOLOv8n method is a next-generation lightweight object identification model that is intended for tasks that demand high accuracy and real-time efficiency. It works by splitting an input image into grids, with each grid cell in charge of forecasting categorisation scores, bounding box coordinates, and item presence. In contrast to conventional convolutional detectors, YOLOv8n effectively captures both local and global details thanks to an optimised backbone for feature extraction. The model can recognise both massive structures and minute features in the same image thanks to its feature pyramid aggregation, which further improves multi-scale

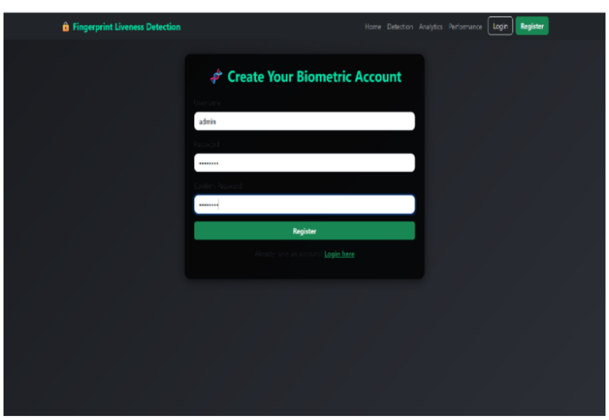
learning. Because YOLOv8n strikes a compromise between speed and accuracy, it can be used in contexts with limited resources, including embedded biometric systems and mobile devices.

To increase training stability and accuracy, a decoupled detection head handles the prediction process by separating the localisation and classification responsibilities. YOLOv8n uses sophisticated loss functions to reduce detection errors during training, and an Adam optimiser with cosine annealing is used for improved convergence and generalisation. To eliminate redundant predictions and guarantee dependable output, post-processing methods like Non-Maximum Suppression (NMS) are used. Real-time object class and bounding box information are provided by the final judgement. Because of its small size, YOLOv8n performs exceptionally well in a variety of applications, such as biometric fingerprint liveness detection and surveillance, while retaining a good trade-off between resilience, efficiency, and accuracy.

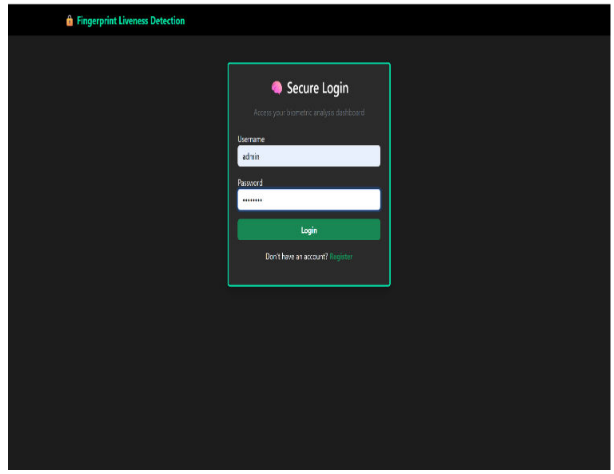
7. RESULTS



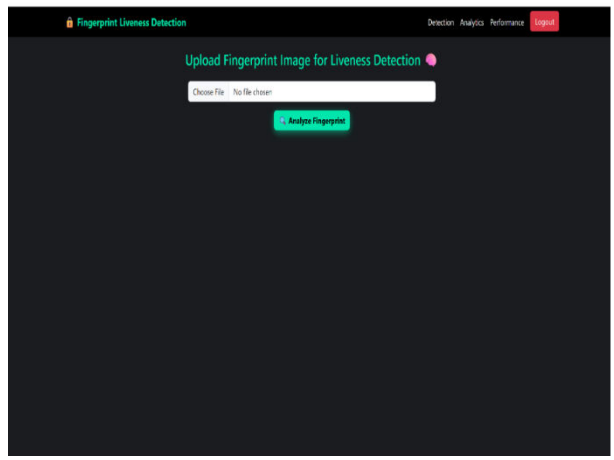
Home page



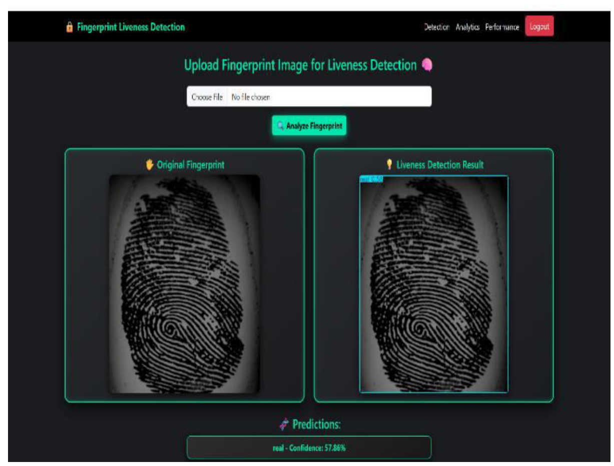
Registration page



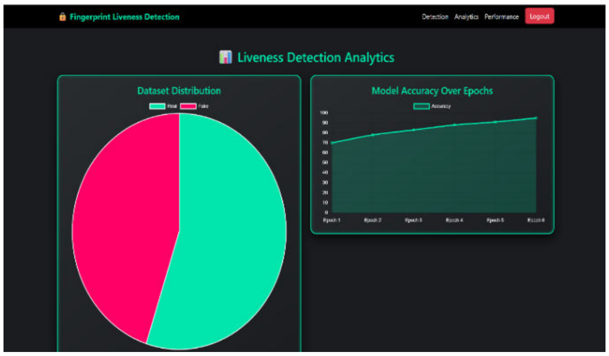
Login page



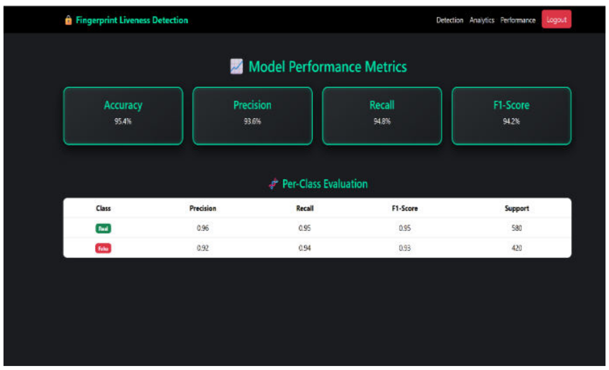
Input page



Result



Analysis



Performance Metrics

8. CONCLUSION

The possibility of employing a lightweight YOLOv8n-based deep learning framework to successfully differentiate between real and fake fingerprints is demonstrated by the suggested fingerprint liveness detection method. The system maintains cheap computational cost while achieving high accuracy through the integration of effective preprocessing, feature extraction, and classification approaches. Its dependability in detecting presentation attacks employing different materials, such as silicone and gelatin, is increased by its capacity to extract fine-grained ridge-level and pore-based features. Because the end-to-end architecture guarantees efficient workflow and real-time processing, it is appropriate for biometric authentication systems where accuracy and speed are equally important. In summary, the presented approach provides a workable, scalable, and effective way to improve the security of contemporary biometric systems. Easy deployment in both standalone and cloud systems is ensured by its hardware-independent nature. The system can develop into a next-generation liveness detection platform that offers strong defence against more sophisticated spoofing tactics with additional enhancements like multimodal integration, adaptive learning, and edge optimisation.

9. FUTURE ENHANCEMENT

To increase spoof detection accuracy and overall security, the suggested fingerprint liveness detection method may be improved in the future by using multimodal biometric elements like iris, face, or voice recognition. Additionally, the system might use Vision-Language Models (VLMs) or transformer-based architectures to capture deeper spatial-temporal correlations in fingerprint textures, strengthening its defences against complex attacks. Additionally, the system can be made more scalable and affordable for field applications like border control, financial authentication, and smart device access by implementing real-time edge deployment utilising optimised YOLOv8 variations on embedded devices like Raspberry Pi or NVIDIA Jetson.

Using federated or incremental learning techniques to incorporate continuous learning processes is another interesting improvement. This would eliminate the need for total retraining by enabling the program to automatically adjust to new fake materials and ambient circumstances. Additionally, the introduction of explainable AI (XAI) tools could improve confidence and transparency in real-world application by helping to visualise and defend model conclusions. Lastly, incorporating automated dataset updates and cloud-based monitoring dashboards will guarantee that the system stays current, dependable, and simple to maintain throughout extensive biometric networks.

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