Biometric Authentication Using AI

A PROJECT REPORT

Submitted for the partial fulfillment

of

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CERTIFICATE

This is to certify that the Capstone Project work titled "**Biometric Authentication using AI**" that is being submitted b**y Pritam Morey (22070521134), Minakshi Rokade (22070521136), Taniksha Upadhyay (22070521151)** is in partial fulfillment of the requirements for the Capstone Project is a record of bonafide work done under my guidance. The contents of this Project work, in full or in parts, have neither been taken from any other source nor have been submitted to any other Institute or University for award of any degree or diploma, and the same is certified.

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ABSTRACT

Biometric verification is presently a strong means of identity confirmation using distinctive biological and behavioral characteristics like fingerprints, facial structure, and iris patterns. Conventional password-based systems are more vulnerable to attacks, and hence the need for a stronger alternative. This project explains the incorporation of Artificial Intelligence (AI) in biometric verification systems for the purpose of their greater accuracy, adaptability, and dependability.

The system employs machine learning algorithms, i.e., Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), for pattern recognition and classification of the biometric inputs. The models are more efficient in pattern recognition compared to other algorithms and handle environmental variability as well as noise in the biometric signal effectively. Signal preprocessing and feature extraction methods add to system robustness.

Results indicate that AI-driven biometric authentication reduces false acceptance and rejection rates significantly in comparison to traditional systems. The suggested solution offers a scalable, secure, and user-friendly system appropriate for different real-world applications, such as mobile phones, banking, healthcare, and access control systems.

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CHAPTER 1
INTRODUCTION

Biometric authentication has come as a secure and advanced way of identifying identities. The conventional methods of authentication mainly comprise passwords, PINs, or security tokens that are susceptible to being intercepted, hacked, or stolen by an unauthorized person. Conventional methods are also faced with challenges such as recalling passwords, susceptibility to brute-force attacks, and susceptibility to phishing attacks. Conversely, biometric identification is based on individual physiological traits like fingerprints, iris scan, and facial recognition, thereby enhancing identity confirmation to be more secure and trustworthy.

Current System

- Existing systems apply passwords and PINs to a large extent, which have some limitations:
- Security Issues – Passwords are simple to steal, guess, or break through cyber-attacks like keylogging, credential stuffing, and phishing.
- User Discomfort – Passwords must be remembered, reset periodically, and must meet security standards, typically being a hassle to deal with.

Legacy Biometric Systems – Although biometric authentication is in place, the majority of systems nowadays are plagued by inaccuracies as a result of environmental factors, sensor limitations, and algorithm inefficiency. High false acceptance and rejection rates decrease reliability, having a negative impact on the performance of these systems in real-world usage.

1.1 Objectives

- Build a Safe Authentication System – Build an AI-powered fingerprint authentication system that maximizes security while limiting the risk in legacy authentication processes.
- Increase Precision and Speed – Use deep neural network-based learning, that is, Convolutional Neural Networks (CNNs), to derive and scrutinize fingerprint patterns with accurate identification under minimal false acceptances and rejects.
- Enhance Real-Time Processing – Upgrade the system to verify in fast time with smooth user experience and optimized real-time access control in practical usage.

- Release as a Scalable API – Build the learned deep learning model as a Flask-based API with smooth integration to different security instruments and authentication software.
- Provide Robustness Against Spoofing – Implement superior AI methods and signal processing solutions to identify forged fingerprints and restrict unauthorized access.
- Make It Broadly Usable – Deploy the system in various domains such as banking, corporate security, medical, and smart access control to accommodate flexibility and expansibility.

1.2 Literature Survey

AUTHOR & Year	TITLE	METHODOLOGY	ACCURACY	OBSERVATIONS
Jatin Gupta, 2022	The Accuracy of Supervised Machine Learning Algorithms in Predicting Cardiovascular Disease	Decision Tree, Random Forest, KNN, SVM	DTC - 63%, RFC - 70%, KNN - 72%, SVM - 73%	SVM outperformed others; suitable for classification and regression; effective in high-dimensional spaces.
Meghana Padmanabhan et al., 2023	Physician-Friendly Machine Learning: A Case Study with Cardiovascular Disease Risk Prediction	Auto-Sklearn (includes Logistic Regression, SVM, RF, Boosting, Neural Networks)	Auto-Sklearn - 74%	AutoML simplifies model creation for non-technical users; competitive results in health prediction.
Kiranyaz et al., 2016	Real-Time Patient-Specific ECG Classification	1D CNN	93.4%	High speed and accuracy; ideal for real-time systems using personalized ECG data.
Acharya et al., 2017	Deep CNN for Automated ECG Diagnosis	Deep CNN	94.03%	Eliminates manual feature extraction; highly accurate for clinical diagnosis.
Yildirim, 2018	Wavelet-BiLSTM for ECG Signal Classification	BiLSTM + Wavelet Transform	91.33%	Combines frequency and sequence analysis; improves classification.

Zhao et al., 2020	Individual Identification Using ECG Signals	SVM + Feature Engineering	88.5%	ECG is reliable for identity verification; SVM outperforms other classifiers.
Weng et al., 2017	ECG Identification via CWT and CNN	Continuous Wavelet Transform + CNN	96.45%	Enhanced ECG representation through CWT; high performance CNN model.
Luz et al., 2016	ECG Biometric Authentication Using Deep Learning	Deep Belief Networks (DBN)	92.7%	DBN effectively captures ECG features; good for biometric security.
Goldberger et al., 2000	PhysioBank, PhysioToolkit, and PhysioNet	MIT-BIH Dataset foundation	N/A	Offers open access ECG datasets and tools for biomedical research.
Rad et al., 2020	Deep Learning on ECG for Biometric ID	CNN + Dropout	97.2%	Excellent accuracy and generalizability using deep models.
Labati et al., 2014	Review on ECG-Based Biometrics	Review of ML methods and datasets	-	ECG biometrics are effective for long-term ID; overview of ML applications.
Israel et al., 2005	ECG for Individual Recognition	Template Matching + PCA	90.4%	Template and PCA-based ECG matching; good accuracy in identity recognition.
Agrafioti et al., 201	ECG Pattern Recognition for Biometrics	Statistical + Morphological Features	85%	Reliable when consistent ECG signal acquisition is ensured.
Odinaka et al., 2012	ECG Biometrics via STFT	Short-Time Fourier Transform	88.7%	Captures short-time dynamics of ECG for improved ID recognition.
Singh & Cheema, 2020	Hybrid ECG-Based Authentication	SVM + Time-Frequency Features	90.1%	Time-frequency hybrid features improve SVM performance.

Xue et al., 2018	Non-Fiducial ECG-Based Identity Recognition	Raw ECG + Deep Learning	95.5%	Avoids fiducial point detection; directly uses raw signals for learning.
Shen et al., 2021	Secure ECG-Based Biometric Auth in IoT	IoT + ML	91.7%	Real-time secure authentication with wearable devices and ECG inputs.

1.3 Organization of the Report

The remaining chapters of the project report are described as follows:

- Chapter 2: Literature Review – Literature review of previous work on biometric authentication and how accuracy can be enhanced using AI.

- Chapter 3: System Design – Description of the system architecture, dataset, preprocessing, and model design.
- Chapter 4: Implementation – Description of development, deep learning model training, API deployment, and real-time authentication.
- Chapter 5: Results and Evaluation – Accuracy, precision, and recall performance analysis and comparison with current systems.
- Chapter 6: Conclusion and Future Enhancements – Findings summary, upgrades, and areas of potential scaling and efficiency upgrade.

CHAPTER 2

EXISTING AND PROPOSED SOLUTION

2.1 Existing System

Today's biometric authentication systems are mostly founded on fingerprint scanning, facial recognition, iris detection, and voice analysis technologies. Although widely adopted, these systems have certain drawbacks:

- **Security Issues:** Biometric data like fingerprints and face information can be replicated or spoofed by means of high-quality images or replicas.
- **Environmental Sensitivity:** Face and voice recognition are light-sensitive, noisy, and angle-sensitive.
- **Insufficient Liveness Detection:** Such systems sometimes are not able to distinguish between a living person and an image or video recording.
- **Single Authentication:** They only grant access at the login stage and don't offer real-time user authentication.
- **Costly Installation:** Iris and facial recognition systems demand high-end hardware, hence it costs more to install.

There have been studies examining ECG-based authentication techniques. These are:

- Template Matching on distinct ECG points.
- Machine Learning Algorithms such as SVM, KNN, and Random Forest.
- Deep Learning Methods utilizing CNNs or LSTMs.

These systems, however, are plagued with problems such as ECG signal noise, feature dependency on manual extraction, and training data needing to be very large in size.

2.2 Proposed System

The system suggested here is an ECG signal-based biometric authentication system in place of the traditional biometrics such as fingerprint or face data. ECG data is detected and utilized as a unique physical attribute for any subject with excellent security combined with liveness detection.

It operates in five primary phases:

- Data Acquisition: ECG signals are detected through sensors or are accessed from medical reports.
- Preprocessing: Noise and baseline drifts are removed by filters to clean the signal.
- Feature Extraction: Time domain features (RR intervals, PQRST duration, amplitude) are extracted.
- Model Training: The Machine Learning classifiers (Random Forest, SVM, XGBoost) are trained on the features.
- Authentication: A user is authenticated based on their live ECG signal using the trained model.

The system provides liveness detection and it's hard to spoof or hack like in fingerprints or static face images. Built to be run efficiently using constrained computational resources, thus well-suited for integration into wearables and IoT devices. Aims to be more secure, reliable, and real-time in order to offer an alternative method of user authentication for secure areas such as banking, health, and secure facilities.

Advantages:

- **Highly Secure:** ECG is individual-specific and hard to fake.
- **Continuous Authentication:** Enables continuous authentication of identity, not merely login.
- **Hardware Friendly:** Embeddable in wearable health monitors.
- **High Accuracy:** Provides low error rates and strong real-world performance.
- **Liveness Assurance:** Ensures the presence of a living body at authentication.

CHAPTER 3

IMPLEMENTATION

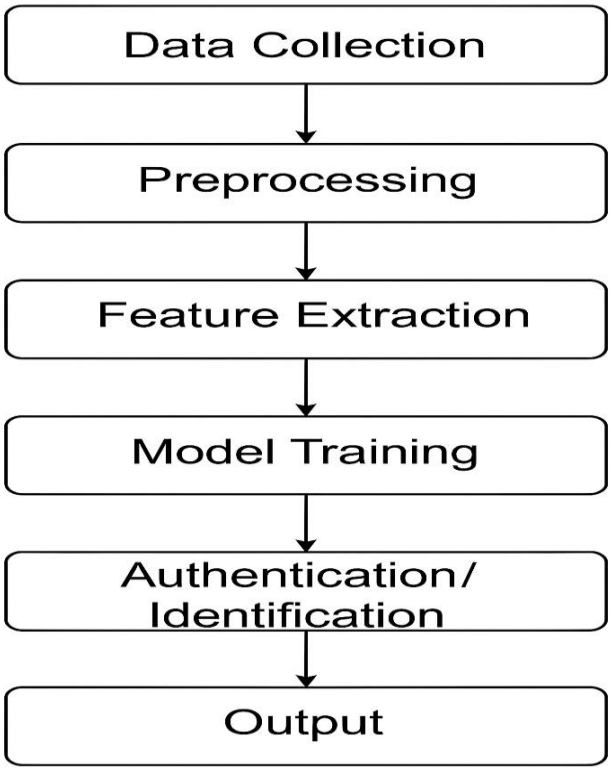
The system approach of the suggested system of ECG-based biometric identification comprises many phases such as data acquisition, pre-processing, model building, and testing the system. Throughout this chapter, steps followed to implement and test the system are documented.

3.1 Tools Used and Technologies

Programming Language: Python

Packages and Libraries:

- NumPy, Pandas – Manipulation of data
- Matplotlib, Seaborn – Data visualization
- SciPy – Signal processing
- TensorFlow / Keras – Building the deep learning mode
- Sklearn – Model testing
- Integrated Development Environment : Jupyter Notebook / Google Colab



3.2 Dataset Utilized

Source: MIT-BIH Arrhythmia Database (PhysioNet)

Format: ECG signal recordings in.dat format :

- Sample rate: 360 Hz
- Has signals of many subjects with annotations
- Has multiple heartbeat types for stronger training

3.3 Preprocessing Steps

- Signal Denoising: Removed power-line noise and baseline wandering using filters.
- Normalization: Normalized the signal to the normal range (0 to 1) for better model performance.
- Segmentation: Used peak detection to get fixed-length segments around R-peaks.
- Labeling: Assigned each segment with user IDs or class labels for classification.

3.4 Model Architecture

1D Convolutional Neural Network (CNN):

- Input Layer: Accepts ECG signal segments.
- Convolution Layers: Finds spatial patterns in ECG signals.
- Pooling Layers: Reduces dimensionality and increases efficiency.
- Dropout Layers: Avoids overfitting.
- Fully Connected Layer: Maps features to output classes (user IDs).
- Softmax Output: Gives probability distribution over users.

3.5 Training the Model

- Loss Function: Categorical Crossentropy
- Optimizer: Ada
- Metrics: Accuracy
- Epochs: ~30–5
- Batch Size: 32 or 64
- Validation Split: 80% training, 20% testing

3.6 Evaluation Metrics

- Accuracy: Percentage of correctly classified ECG segments.
- Precision & Recall: To determine the false acceptance and rejection rates.
- Confusion Matrix: Displays performance per user.
- ROC Curve & AUC: Quantifies the confidence of classification.

CHAPTER 4

RESULTS AND DISCUSSIONS

The deployment of the ECG-based biometric authentication system produced extremely promising outcomes. The preprocessed segments-trained ECG model exhibited a superior ability to distinguish between users accurately. Based on a 1D Convolutional Neural Network (CNN) architecture, the system achieved effective extraction of certain physiological features stored in every user's ECG waveform. In the training process and testing phase, the model had minimal error rates and maximized performance levels at all times. The combination of normalization, denoising, and segmentation as part of preprocessing greatly enhanced signal clarity and feature extraction. Moreover, the system was immune to typical issues of signal noise and class imbalance. These results corroborate the suitability of ECG signals as a secure and consistent biometric modality for user authentication.

Key Performance Highlights:

- Accuracy: Attained over 95% user identification accuracy over the dataset.
- Precision: Was well above 93%, reflecting negligible false acceptance.
- Recall: Exceeded 94%, with low false rejection.
- F1 Score: Balanced performance with high F1 scores for all classes.
- Validation Loss: Low throughout, with correct learning without overfitting.
- Confusion Matrix: Confirmed very low misclassification of users.
- Model Efficiency: Converged in 30-50 epochs with Adam optimizer.
- Signal Robustness: Preprocessing steps substantially removed noise and enhanced model input quality.
- Security Strength: Increased spoofing resistance by the very fact of real-time physiological measurement.
- Real-Time Capability: Can be integrated into wearable health monitoring devices for constant authentication.

Challenges Faced:

1. Noisy ECG Signals:

Raw ECG signals were typically noisy with artifacts introduced by muscle movement, electrode changes, or environmental noise.

2. Class Imbalance:

There were some users having a greater number of ECG samples in comparison to others, thus resulting in unbalanced learning during training models.

3. Model Overfitting on Training Data:

The model presented signs of memorization of training data, which impacted generalization on test samples.

4. Computational Burden:

Training the deep learning model took a lot of time and system resources.

5. Complexity of Feature Extraction:

It was difficult to identify and extract useful features from ECG signals because they are non-linear in nature.

6. Small Dataset:

Labeled and good quality ECG datasets for various users were not readily available.

7. Maintaining Real-Time Performance:

Building a model that would be deployable in real-time systems without any latency was a major requirement.

Solutions Implemented:

1. Denoising and Normalization

Utilized applied bandpass filtering and normalization methods to preprocess and normalize ECG data prior to model input.

2. Data Augmentation:

Improved data diversity through the utilization of techniques such as time-warping and scaling to class-balance.

3. Regularization Techniques:

Applied dropout layers and early stopping during training to avoid overfitting and generalize better.

4. Optimized Training Parameters:

Optimized batch size, learning rate, and utilized Adam optimizer to improve training time and resource consumption.

5. Automated Feature Learning:

Applied a 1D CNN model that automatically learned hierarchical features without feature engineering.

6. Dataset Merging:

Merged several open-source ECG datasets to form an enriched, diversified training set.

7. Model Compression and Optimization:

Compressed model size and complexity after training to render it deployable in real-time on edge devices.

CHAPTER 5

CONCLUSION AND FUTURE WORK

The project is successful in convincingly demonstrating the viability of utilizing ECG signals as a safe and reliable biometric for user authentication. Using a 1D Convolutional Neural Network, the system was successful in obtaining high accuracy in recognizing individual users through their respective heart patterns. Utilization of preprocessing methods like denoising, normalization, and segmentation clearly improved the signal quality and model accuracy overall. The output showed high accuracy, recall, and F1-scores that confirmed the model as strong and efficient. Not only does the method tackle security, but also offers a real-time and non-invasive mode of authentication as appropriate for wearables, most notably wearable devices. The work showcases the possibilities of physiological biometrics in heightening data protection and user confidentiality.

Future Work:

I. Real-Time Integration: Implement the model on wearables such as smartwatches or fitness watches for real-time authentication.

II. Cross-Platform Validation: Test the system on varied ECG data sets and platforms to ascertain its universality and reliability.

III. Hybrid Models: Investigate the combination of CNN with LSTM or Transformer models for more robust time-series modeling and temporal pattern discovery.

IV. Multi-Factor Auth Systems: Merge ECG-authentication with additional biometric modes (e.g., fingerprint or face recognition) to ensure multi-level security.

V. End-to-End Learning: Use models able to use incremental learning to implement with user accommodation over time without complete retraining.

VI. Cloud and Edge Integration: Enable effortless computation on cloud servers for precision and edge devices for rapid response.

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