Thakur Educational Trust's (Regd.)
THAKUR COLLEGE OF SCIENCE & COMMERCE
Empowered Autonomous College Permanently Affiliated to University of Mumbai
(NAAC Accredited with Grade "A" (3rd Cycle) & ISO 21001:2018 Certified)
Best College Award by University of Mumbai for the Year 2018-2019

A Project Report on

Signature Verification Using ML For Reducing Bank Fraud

Submitted By

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Under the esteemed guidance of

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(Assistant Professor)

Submitted in Partial Fulfilment of the requirement for qualifying

BACHELOR OF SCIENCE (DATA SCIENCE)

Semester – VI Examination

THAKUR COLLEGE OF SCIENCE AND COMMERCE

(Autonomous College, Affiliated to University of Mumbai)

THAKUR VILLAGE, KANDIVALI(E),

MUMBAI, 400 101 MAHARASHTRA

2024 -2025

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Certificate

This is to certify that the project entitled "**Signature verification using ML for Reducing Bank Fraud**" undertaken at Department of Science (DS) at Thakur College of Science and Commerce by Mr. Shivam Vishwakarma and Mr. Utkarsh Yadav of Class TYDS (A) Roll No. 2823 and 2821 in partial fulfilment and implementation of BSc (DS) degree (Semester VI) has satisfactorily completed the final year project.

Signature	Signature
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Acknowledgement

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"We extend our sincere thanks to our principal, "**Dr. (Mrs.) Chaitali Chakraborty"**, who played a crucial role in making this project a reality, by giving us a platform to express our perspectives and ideas. We express our gratitude for her indispensable contributions."

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Declaration

We hereby declare that the project entitled, '**Signature Verification Using ML For Reducing Bank Fraud'** is done at **Thakur College of Science and Commerce**, this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that We have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. We understand that any violation of the above will cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Date:
Place: Mumbai

_____
Signature

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Abstract

Financial fraud, particularly signature forgery, poses a significant threat to banking and financial institutions. Traditional manual verification methods are prone to human error and inefficiencies, leading to security vulnerabilities. This project presents a Signature Verification System leveraging Machine Learning (ML) and Image Processing techniques to enhance fraud detection accuracy. The system processes scanned cheque images, extracts signatures using Optical Character Recognition (OCR), and verifies authenticity through Support Vector Machine (SVM) classification.

The methodology involves preprocessing, feature extraction, and classification to differentiate between genuine and forged signatures. Additionally, the Line Sweep Algorithm enhances detection accuracy by isolating signature regions. Implemented using Flask, Python, OpenCV, and TensorFlow/Keras, the system provides an automated, scalable, and secure approach to financial fraud prevention. The integration of database-backed user authentication ensures data security, while a web-based interface allows seamless user interaction.

Experimental results demonstrate improved accuracy in detecting forged signatures, reducing false positives and negatives. This system offers a cost-effective, automated alternative to manual verification, significantly minimizing financial fraud risks in banking and commercial transactions.

INTRODUCTION

In today's rapidly evolving digital economy, the financial sector has seen significant advancements in technology, but it remains vulnerable to fraud, particularly in areas involving personal authentication, such as signature verification. Signatures have long been used as a standard method for validating identities in financial transactions, such as cheque processing, contracts, and loan applications. However, the traditional reliance on manual verification of handwritten signatures has become increasingly insufficient in the face of sophisticated forgery techniques. As fraudulent activities become more elaborate, there is a growing need for more advanced, automated methods of verification that are both reliable and efficient.

The manual process of verifying signatures is labor-intensive and prone to human error, especially when bank officials have to handle thousands of signatures daily. Variations in handwriting, changes in personal habits, or even fatigue on the part of human verifiers can lead to errors in judgment, resulting in forgeries being overlooked or genuine signatures being flagged as fraudulent. This not only delays transactions but also opens up the banking system to financial losses caused by fraudulent activities. Consequently, financial institutions are actively seeking ways to enhance the accuracy and speed of the signature verification process while reducing the potential for human error.

Machine learning (ML) has emerged as a powerful tool in addressing these challenges. ML allows systems to learn from data, identify patterns, and make decisions with minimal human intervention. In the context of signature verification, machine learning offers the ability to develop systems capable of analyzing and verifying signatures with a high degree of accuracy by learning the unique characteristics of an individual's handwriting. These characteristics might include pen pressure, stroke speed, signature shape, and other distinguishing features that are hard to replicate convincingly in a forgery. By analyzing these features, an ML-based system can automatically distinguish between genuine signatures and forgeries, offering an efficient and reliable solution to a growing problem in the banking sector.

A typical signature verification system using machine learning consists of several stages. First, a dataset of signatures—both genuine and forged—is collected and preprocessed. This step

may involve cleaning the data, removing noise from the images of signatures, and normalizing the data to ensure consistency. Once the data is ready, the system proceeds with feature extraction, where specific traits of each signature are analyzed. These traits may include the shape, angles, pressure patterns, and dynamics of the signature. This is typically achieved using convolutional neural networks (CNNs), which are well-suited for image-based tasks such as signature recognition. CNNs can extract complex features from images, which are then used to train the machine learning model.

The next step involves training the model using supervised learning, where it is fed labeled data—examples of both authentic and forged signatures. Over time, the model learns to recognize the patterns that distinguish genuine signatures from forgeries. Once trained, the model can be tested on new, unseen signatures to evaluate its performance. The final stage involves fine-tuning the model to improve its accuracy and reduce false positives (genuine signatures incorrectly flagged as fraudulent) and false negatives (fraudulent signatures that pass as authentic). The ultimate goal is to create a system that can verify signatures in real time, helping banks detect and prevent fraudulent activities before they cause harm.

This ML-based system offers several advantages over traditional signature verification methods. Firstly, it provides greater accuracy by minimizing the chances of human error. Secondly, it significantly reduces the time required for verification, as the system can process thousands of signatures in a fraction of the time it would take a human verifier. Additionally, the system can be continuously updated with new data, allowing it to adapt to evolving forgery techniques and become more robust over time. This adaptability is crucial in a landscape where criminals are constantly developing new methods to bypass security measures.In the context of financial fraud prevention, the impact of such a system is immense. By reducing the likelihood of forged signatures being accepted as genuine, banks can mitigate the risk of fraudulent transactions, saving both money and reputation. Furthermore, the automation of the verification process can lead to operational cost savings, as fewer human resources are required to perform manual checks. Customers also benefit from faster transaction processing times and increased confidence in the security of their financial interactions.

OBJECTIVE

The primary objective of this project is to develop a robust machine learning model that accurately verifies signatures to reduce the risk of financial fraud in the banking sector. The verification model will help banks identify and prevent fraudulent transactions by distinguishing between genuine and forged signatures. By understanding the unique characteristics of signatures, the system can provide timely intervention to ensure the security and authenticity of financial documents, ultimately enhancing trust and reducing fraudulent activities.

1. Develop a Predictive Signature Verification Model: Utilize machine learning techniques and historical signature data to build a model that can accurately differentiate between genuine and forged signatures. The model should provide actionable insights by assigning confidence scores to the authenticity of each signature.
2. Identify Key Signature Features: Analyze signature patterns to determine key features that distinguish genuine signatures from forgeries. These may include factors such as stroke pressure, speed, angle, shape, and overall structure. Understanding these key indicators will improve the model's accuracy in detecting fraudulent signatures.
3. Reduce Financial Fraud: Implement the signature verification model to identify potentially fraudulent signatures and prevent unauthorized transactions. The goal is to reduce the overall rate of financial fraud by detecting forgeries early in the verification process.
4. Enhance Security and Customer Trust: By preventing signature forgeries and ensuring the authenticity of financial transactions, the model will help banks build stronger relationships with their customers by increasing trust in the security of their services.
5. Evaluate and Continuously Improve the Model: Regularly evaluate the performance of the signature verification model using metrics such as accuracy, precision, recall, and F1-score. The model should be updated and refined over time based on new signature data and evolving forgery techniques to maintain its effectiveness in preventing fraud.

SCOPE

Scope of Signature Verification Using Machine Learning:

The scope of this project encompasses the entire process of developing and implementing a signature verification model using machine learning to prevent financial fraud in the banking sector. It begins with data collection, where a dataset of genuine and forged signatures will be gathered from the bank's records and other relevant sources. This dataset will serve as the foundation for analyzing signature patterns and understanding the distinguishing features that separate authentic signatures from forgeries. Ensuring data quality and completeness will be a key focus to facilitate accurate analysis and effective model training.

Once the signature data is collected and preprocessed, the next phase involves feature extraction and the selection of appropriate machine learning algorithms. Key features, such as stroke dynamics, pen pressure, angle, and overall shape, will be identified and extracted to improve model accuracy. Various machine learning algorithms, including convolutional neural networks (CNNs), support vector machines (SVMs), and other deep learning methods, will be explored to determine which provides the highest accuracy in identifying forged signatures.

The model will be trained on a portion of the signature dataset and validated on a separate test set to evaluate its effectiveness in preventing fraud.

The final scope includes the deployment of the signature verification model into the bank’s operational environment. This will involve creating an interface or system integration where bank staff can access the model’s predictions and use the insights to verify signatures quickly and accurately. Overall, the project aims to provide a comprehensive solution that enhances fraud prevention, reduces manual workload, and improves the overall security of banking transactions by automating signature verification through machine learning.

PROBLEM DEFINITION

In the e-commerce sector, customer churn poses a significant challenge that can adversely affect revenue and growth. High churn rates indicate that customers are not finding enough value in the products or services offered, leading to increased acquisition costs as businesses strive to replace lost customers. This cycle of acquiring new customers while simultaneously losing existing ones can lead to instability in sales and profitability, making it essential for businesses to understand and address the factors contributing to churn.

The lack of actionable insights into customer behavior and preferences further exacerbates the churn problem. Many e-commerce platforms collect vast amounts of data, yet often struggle to extract meaningful patterns that can predict churn effectively. Without a predictive model, businesses may miss opportunities to engage at-risk customers before they decide to leave, resulting in a reactive rather than proactive approach to customer retention.

Consequently, companies need a systematic way to analyze customer data, identify churn indicators, and implement targeted retention strategies.

This project aims to address these issues by developing a machine learning-based churn prediction model tailored to the specific needs of the e-commerce platform (Note: By specific we mean general model what can be used by any ecommerce sector which can provide necessary data for model to run). By leveraging historical customer data and advanced analytical techniques, the project seeks to uncover the underlying causes of churn and enable the business to act on these insights. The goal is to create a sustainable customer retention strategy that minimizes churn rates, enhances customer satisfaction, and ultimately drives long-term profitability. Through this comprehensive approach, the e-commerce business will be better positioned to navigate the competitive landscape and maintain a loyal customer base.

Feasibility Study

Technical Feasibility

The development team is proficient in Python, which will be the primary programming language for signature data handling, machine learning model development, and deployment. The project will utilize open-source libraries like Pandas for data manipulation, Scikit-learn for model development, and Keras or TensorFlow for deep learning algorithms like Convolutional Neural Networks (CNNs). This ensures there are no additional licensing costs. The team also has access to cloud infrastructure, ensuring the system can scale as needed, especially when handling large datasets of signatures for training and verification.

Operational Feasibility

The system will integrate seamlessly into the existing banking processes for signature verification. It will provide actionable insights for bank staff by verifying signatures quickly and accurately without disrupting their workflow. The system will be designed with a user-friendly interface, ensuring that minimal training is required for end-users such as bank tellers or fraud detection teams. The system will improve operational efficiency by automating a traditionally manual task, reducing the time required for signature verification and improving fraud detection accuracy.

Economic Feasibility

The cost of developing the system includes resources for data scientists, software engineers, and cloud infrastructure for hosting the model. However, the potential cost savings from reduced fraudulent transactions, improved operational efficiency, and enhanced security far outweigh the development costs, making the project economically feasible. By preventing fraud, banks can avoid significant financial losses and reduce the burden on their fraud detection teams.

Legal Feasibility

Protecting your privacy: The system will comply with all relevant data protection laws, such as the General Data Protection Regulation (GDPR) or local banking regulations, to ensure customer signature data is handled securely.

Regulatory compliance: The system will be designed to meet all relevant banking and financial regulations, ensuring its legality and security when deployed in operational environments.

Licensing: Any third-party libraries or tools used in the project will comply with open-source licensing agreements, ensuring proper legal use. are in order.

Inclusions

Signature verification using machine learning models like CNN and SVM.

Predictive analytics based on genuine and forged signature datasets

Web-based dashboard for visualizing signature verification results and managing flagged transactions.

Exclusion

Does not include external marketing campaign management.

Does not focus on acquiring new customers (only retention).

STEPS

Steps to Make Signature Verification Model Using Machine Learning

Project Initiation

i. Define the project objectives and scope, focusing on reducing banking fraud through automated signature verification.

ii. Identify key stakeholders, including bank officials, IT teams, and fraud detection experts, and form a project team.

iii. Conduct a feasibility analysis to ensure resources (data, expertise, and infrastructure) are available to build the system.

Data Collection

i. Gather a comprehensive dataset of both genuine and forged signatures from multiple sources, including:

ii. Historical banking records of signatures.

iii. Handwritten signature images across various formats (cheques, contracts), and signer demographics.

iv. Ensure data privacy and compliance with relevant banking regulations (e.g. data security and confidentiality).

Data Preprocessing

i. Clean the dataset by addressing issues such as missing values, poor image quality, duplicates, and inconsistencies.

ii. Normalize and standardize the signature images (e.g., resizing, contrast enhancement).

iii. Convert image data into numerical features suitable for machine learning models.

Exploratory Data Analysis (EDA)

i. Perform EDA to uncover patterns in the signature data and identify potential distinguishing factors between genuine and forged signatures.

ii. Visualize the characteristics of signature images, such as stroke width, speed, and pressure variations, to understand distribution and correlations.

iii. Determine potential fraud indicators based on insights gained from EDA.

Feature Engineering

i. Select relevant features such as stroke dynamics, angles, pressure points, and signature curvature for the model.

ii. Create additional features like pen-lift frequency, signing speed, or area coverage that may enhance model performance.

iii. Evaluate feature importance to prioritize the most influential factors in detecting forged signatures.

Model Selection

i. Explore various machine learning and deep learning algorithms, including:

ii. Convolutional Neural Networks (CNNs) for image-based feature extraction.

iii. Support Vector Machines (SVMs) for classification tasks.

iv. Random Forest or Decision Trees for traditional machine learning comparisons.

v. Line Sweep Algorithm, OCR Algorithm.

vi. Select the most suitable algorithms based on the nature of the signature data and project goals.

Model Training and Validation

i. Split the dataset into training, validation, and testing sets to ensure robust model evaluation.

ii. Train the selected models on the training data and fine-tune hyperparameters for optimal performance.

iii. Validate the models using appropriate metrics such as accuracy, precision, recall, F1-score, and AUC-ROC.

Model Evaluation

i. Assess the final model on the test dataset to evaluate its ability to detect forgeries accurately.

ii. Use cross-validation techniques to ensure the model's robustness and generalizability.

iii. Analyze the model's strengths and weaknesses, including false positives and false negatives, to fine-tune it further.

Deployment

i. Integrate the signature verification model into the bank’s existing transaction systems for real-time fraud detection.

ii. Create a user interface for bank employees to access the model's predictions, enabling quick verification of flagged signatures.

iii. Develop documentation and user guides for the model’s usage, explaining how to interpret the outputs and confidence scores.

Monitoring and Maintenance

i. Establish a feedback loop to continuously monitor the model's performance and its accuracy in real-world scenarios.

ii. Periodically update the model with new data to account for evolving fraud techniques and ensure continued relevance.

iii. Gather feedback from users (e.g., bank employees) and refine the model as needed based on their experience.

Training and Implementation

i. Conduct training sessions for bank staff on how to use the signature verification system and interpret its outputs.

ii. Implement fraud prevention strategies based on the model’s predictions, such as flagging suspicious transactions for review.

iii. Track the effectiveness of these strategies and adjust them based on fraud detection performance.

Analysis and Prediction

i. Compile a final report summarizing the project outcomes, key insights, and the signature verification system's performance on a user-friendly interface.

ii. Present findings to stakeholders and discuss the next steps for continuous improvement in fraud prevention using the model.

Requirements

Functional Requirements

Functional requirements describe the specific behavior, actions, and functions the system must perform for signature verification and fraud prevention.

Data Requirements:

- The system must have access to historical signature data, including:
- Genuine and forged signature samples across various financial documents (cheques, agreements).
- Metadata related to signatures, such as signing method (manual/digital), timestamp, and document type.
- Signature characteristics such as stroke patterns, pressure, and curvature.
- The data must be pre-processed to handle issues like missing or corrupted signature images, normalize image sizes, and convert signature images into machine-readable formats for the model.

Signature Verification Model:

- The system must build a machine learning model capable of accurately distinguishing between genuine and forged signatures.
- The model must allow for the exploration of various machine learning and deep learning algorithms (e.g., Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), OCR, Line Sweep, Random Forests etc.).
- The model must assign an authenticity probability score to each signature based on the extracted features from the historical signature data.

Feature Engineering:

- The system must allow for the selection and extraction of relevant signature features such as stroke direction, pressure points, signing speed, and pen-lift occurrences.
- The system must allow for feature importance analysis to prioritize the most relevant variables in detecting signature forgeries.

Model Evaluation:

- The model must be evaluated using standard performance metrics, such as accuracy, precision, recall, F1-score, and AUC-ROC, to ensure reliability.
- The system must support cross-validation techniques to validate model robustness and ensure it performs well on unseen data.

Model Deployment:

- The model must be integrated into the bank's existing fraud detection system, making it accessible to authorized stakeholders (e.g., fraud detection teams, bank tellers).
- The system must include an interface where users can view signature verification results, confidence scores, and associated reports.

Fraud Prevention and Intervention:

- Future prospect: The system should provide recommendations for preventing fraud based on signature verification results, such as flagging suspicious signatures for manual review.
- The system must track the effectiveness of fraud prevention strategies implemented because of the model's predictions and adjust recommendations accordingly.

Non-Functional Requirements

Non-functional requirements define the overall qualities and characteristics of the system for signature verification using machine learning to reduce banking fraud.

- Performance:
  - The system must process large volumes of signature data efficiently and provide real- time or near real-time verification results.
  - The system must process large volumes of signature data efficiently and provide real- time or near real-time verification results.

- Scalability:
  - The system must be able to scale as the number of signatures increases, especially with growing banking transactions.
  - The model must accommodate an increasing number of signature data points and metadata as the bank expands and more customers are onboarded.

- Accuracy:
  - Regular updates and retraining should be conducted to maintain the model's accuracy as new signature data and fraud techniques emerge.
  - The signature verification model should aim for a high accuracy rate (e.g., >90%) and minimize false positives (genuine signatures flagged as forged) and false negatives (forged signatures not flagged).

- Security and Privacy:
  - Signature data must be anonymized where possible, and access to sensitive information should be restricted to authorized bank personnel only.
  - The system must ensure that all signature data is securely stored and transmitted, adhering to relevant banking and data protection regulations (e.g., GDPR, financial compliance standards)

- Usability:
  - The system interface for accessing signature verification results must be user- friendly and intuitive, allowing non-technical users, such as bank tellers and fraud analysts, to interpret the model’s outputs easily.
  - The system should provide clear, actionable insights (e.g., risk scores) so that users can quickly determine whether a signature is likely forged.

- Maintainability:
  - The system should be easy to maintain and update as new data or fraud patterns arise.
  - Detailed documentation must be provided for developers, data scientists, and end- users to support ongoing system enhancements and troubleshooting.
- Integration:
  - The system must integrate seamlessly with the bank's existing infrastructure, including transaction processing systems and fraud detection platforms, ensuring smooth operation across multiple departments.
  - Future prospect: The system should support the integration of third-party tools or platforms for fraud detection and risk management, allowing for easy data import/export and compatibility with evolving technologies

Technical Requirements

Technical requirements specify the technologies, tools, and platforms that will be used to develop and deploy the signature verification model to reduce banking fraud.

Data Processing:

- Tools such as Python for data preprocessing, analysis, and model building.
- Libraries like Pandas and NumPy for data handling, OpenCV for image processing, Keras/TensorFlow for machine learning, and Matplotlib for data visualization.
- The model should also utilize Scikit-learn for data splitting, model evaluation, and algorithm comparison.

Modelling Environment:

- Jupyter Notebooks/lab for interactive development and testing of signature verification models.
- VS Code for maintaining organized and well-formatted code, efficiently using libraries, and collaborating across team members.

Database Management:

- As we are using historical signature data, initial storage will rely on Excel files or CSVs that can be imported into Python for further preprocessing.
- A database system like SQLite or MySQL could be implemented in the future to store a large volume of verified signatures securely.

Version Control:

- Git for source code management and version control throughout the project development phase

Deployment and Monitoring:

- Deploy the signature verification model using Flask to serve as a web-based API for integration into the bank's system.
- Create the user interface with HTML and CSS for bank staff to upload signature images and view verification results.
- Future Prospect: Implement monitoring tools like Prometheus or ELK Stack to track the system’s performance and monitor the health of the signature verification model after deployment.

Regulatory Requirements

Data Protection Compliance:

- Ensure compliance with banking and data protection regulations such as GDPR (General Data Protection Regulation), ensuring all customer signature data is securely processed and stored.
- Adhere to financial data privacy standards, limiting access to sensitive data only to authorized personnel and encrypting sensitive information.

Third-Party Agreements:

- Establish data processing agreements with any third-party services that may be involved in storing, processing, or analyzing signature data to ensure legal and regulatory compliance

Software and Hardware Requirements

Hardware Requirements

- Processor: Intel Core i5 (or higher).
- RAM: 16 GB recommended.
- Storage: 500 GB SSD for data storage and model artifacts.

Software Requirements

- Operating System:
  - Windows 11, ensuring compatibility with the development tools and technologies used in the signature verification project.
- Programming Language:
  - Python 3.8+ for developing machine learning models, image processing, and data handling.
- Data Libraries:
  - Pandas and NumPy for data manipulation and preprocessing.
  - Scikit-learn for implementing machine learning algorithms and evaluation metrics.
  - OpenCV for image processing to handle signature images.
  - TensorFlow/Keras for building deep learning models (e.g., CNNs) for signature verification.
  - Matplotlib for visualizing results and model performance.
  - Flask for deploying the signature verification model as a web service.
- Development Environment:
  - Jupyter Notebook for interactive model development and testing.
  - VS Code for structured code management, efficient use of libraries, and collaboration across the project team.
- User Interface:
  - HTML and CSS for building the web interface where bank staff can upload signature images and view verification results.
- Version Control:
  - GitHub for source code management, collaboration, and version control throughout the project lifecycle.
- Deployment:
  - Deploy the signature verification model on Heroku to make it accessible as a web application for real-time use in banking operations.

Data Description

The dataset used in SigniFi comprises genuine and forged signatures collected from various individuals to train and test a machine learning model for fraud detection in banking transactions.

Data Sources

- Augmented signatures using transformations (e.g., rotation, noise addition, blurring) to simulate forgeries.
- Publicly available signature datasets.
- Data collected from different websites and GitHub repositories to train the model.

Data Format

- Image format: PNG, JPG, or TIFF.
- Size: 256x256 or higher (pre-processed).
- Grayscale/Binary: Pre-processed into grayscale or binary for feature extraction.

Features and Attributes

Feature Name	Description
Signature_ID	Unique identifier for each signature image.
User_ID	Unique identifier for the signer.
Image_Path	File path to the stored signature image.
Label	Binary classification: (1 = Genuine, 0 = Forged).
Pressure Variation	Variations in pressure applied while signing.
Stroke Direction	The direction and flow of strokes in the signature.
Aspect Ratio	Width-to-height ratio of the signature.
Contour Features	Extracted contour properties of the signature.
Pixel Density	Number of black pixels in binarized images.
HOG Features	Histogram of Oriented Gradients (used for edge detection).
SIFT/ORB Keypoints	Feature keypoints extracted for comparison.
Time Taken (if available)	Duration taken to complete the signature (if dynamic data is used).

Data Preprocessing

- Resizing & Normalization: Images resized to a fixed size (e.g., 128x128 or 256x256).
- Binarization: Converting grayscale images to black-and-white (thresholding).
- Noise Removal: Using Gaussian blur or median filtering.
- Feature Extraction: Extracting hand-crafted features (HOG, SIFT, ORB) along with deep-learning-based embeddings.

Labels

- 1 (Genuine Signature) – Authentic signature provided by the account holder.
- 0 (Forged Signature) – Fraudulent signature detected from an imposter.

Model Training & Evaluation Data

- Training Data: 70% of the dataset.
- Validation Data: 15% for hyperparameter tuning.
- Testing Data: 15% for final model evaluation.

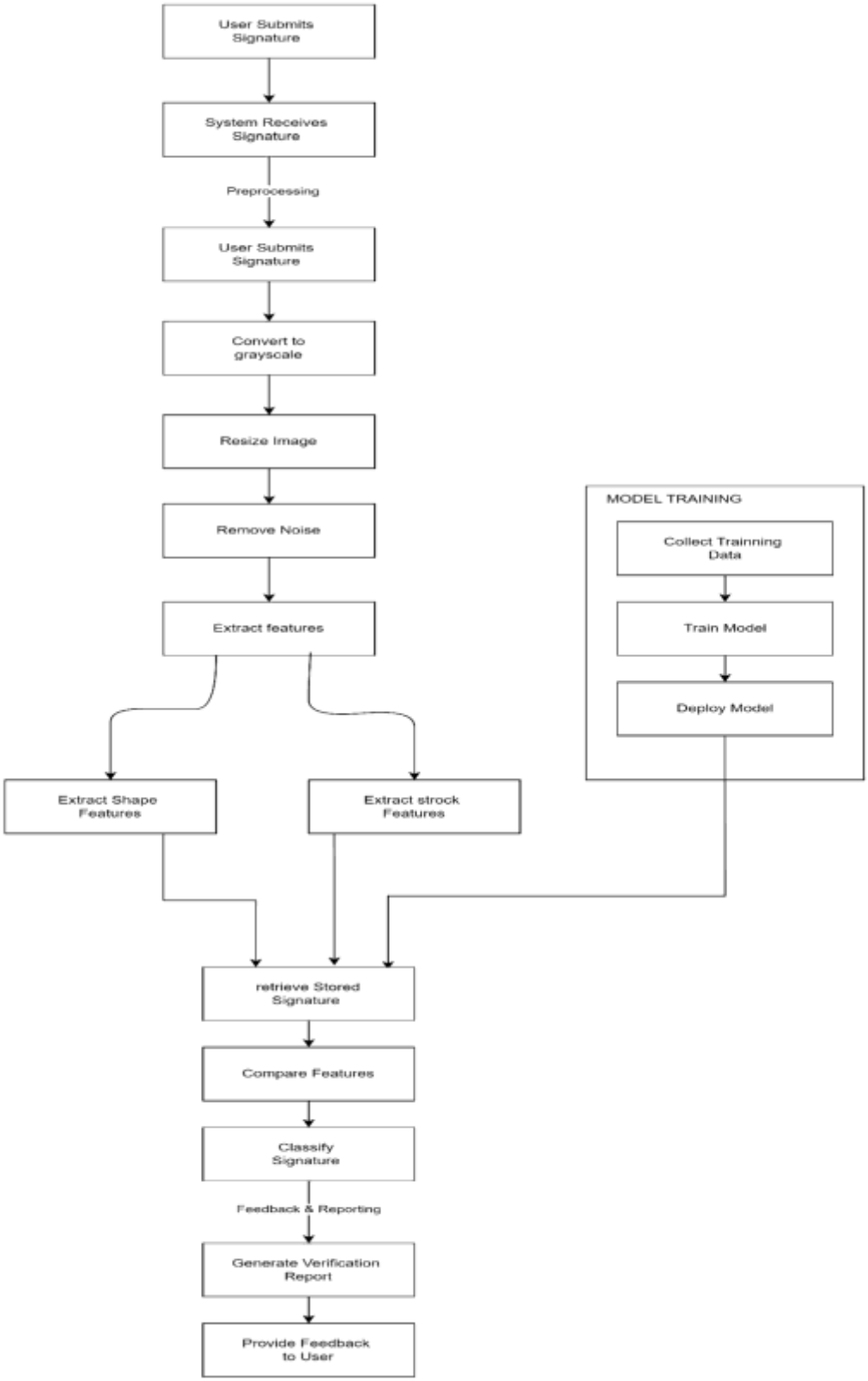
Expected Challenges

- Variability in handwriting styles: Users' signatures may change slightly over time.
- Forgery complexity: Skilled forgeries may closely resemble genuine signatures.
- Data imbalance: Genuine signatures are more common than forged ones, requiring techniques like SMOTE (Synthetic Minority Over-sampling) to balance.

System Analysis and Diagram

LIFE CYCLE OF PROJECT

Each phase is shown as a labeled rectangular box with arrows indicating the sequential flow between stages. Here is a breakdown of the stages in the diagram:

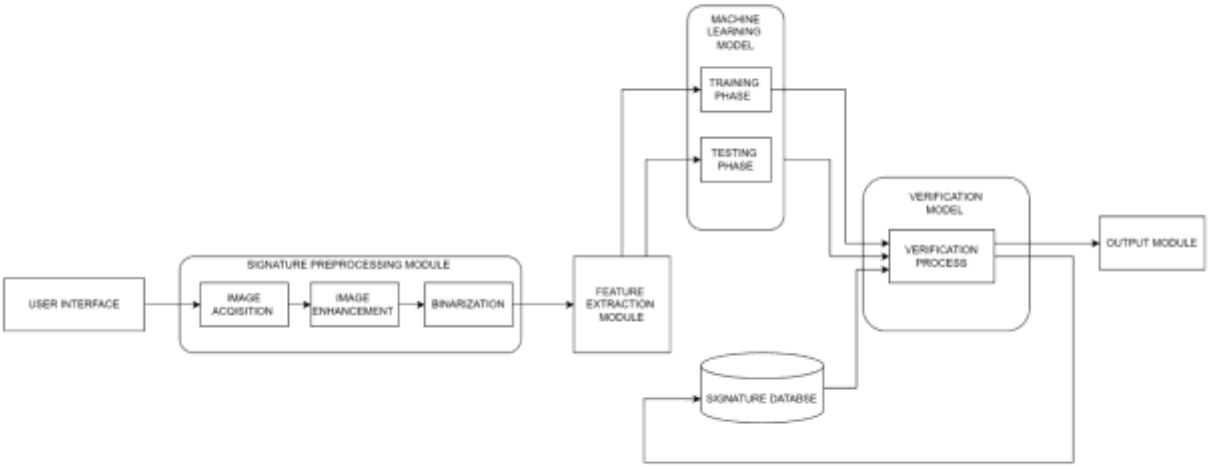


1. Signature Capture:
   - The user submits their signature through the system interface. The system captures and stores the signature for further processing.
2. Preprocessing:
   - The system prepares the signature for analysis by converting it to grayscale, resizing it to a standard size, removing noise, and extracting relevant features for the next step.
3. Feature Extraction:
   - Important characteristics of the signature, such as shape and stroke details, are extracted. These features are critical in distinguishing between genuine and forged signatures.
4. Model Training:
   - Historical signature data is collected to train the machine learning model. The trained model is deployed for live signature verification based on the extracted features.
5. Signature Verification:
   - The system retrieves stored signatures from the database, compares extracted features, and classifies the input signature as authentic or forged based on the model's predictions.
6. Feedback and Reporting:
   - After classification, the system generates a verification report for the user. It also stores the verification data and provides feedback for ongoing model improvements.

The arrows between the boxes represent the progression from one stage to the next, with the dotted arrows showing the iterative nature of the process, where phases like Testing and Development might loop back based on feedback and necessary changes.

This flow reflects the Agile methodology, allowing for flexibility and adaptation throughout the development lifecycle. The focus is on continuous improvement, user-centric design, and the ability to quickly respond to change

Architecture Diagram



The diagram illustrates the architecture of a signature verification system using machine learning. Here's an explanation in six key points:

i. User Interface: The process starts with the user interface, where the user inputs the signature, typically through a scanning or digital input device.

ii. Signature Preprocessing Module: This module handles image acquisition (capturing the signature), enhancement (improving the quality for analysis), and binarization (converting the image to a binary format to focus on signature features).

iii. Feature Extraction Module: After preprocessing, key features of the signature are extracted. These features are the crucial patterns and characteristics that the machine learning model will use for training and verification.

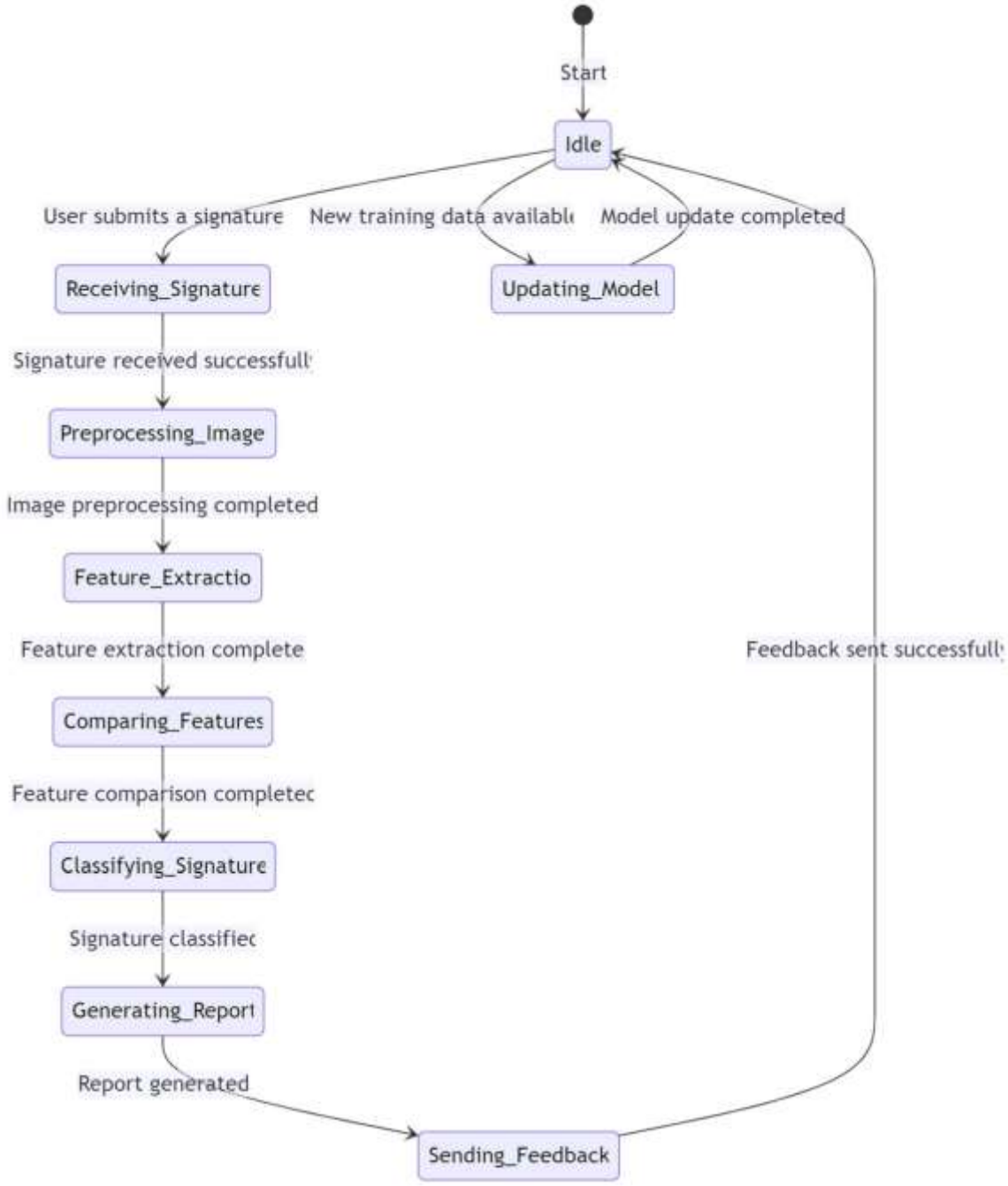
iv. Machine Learning Model (Training & Testing Phases): The extracted features are fed into a machine learning model, which undergoes a training phase using a labeled signature database. In the testing phase, it evaluates new signatures against this trained model.

v. Signature Database: This stores both the original signatures and their extracted features for comparison during the verification process.

Verification Model and Output: The verification process compares the new signature to the stored data, determining its authenticity. The result is then passed to the output module, which provides feedback to the user, such as whether the signature is verified or not.

Process Diagram

A process diagram is a graphical representation of a sequence of activities or steps that are performed to achieve a specific outcome



Explanation:

Data Collection: The process begins with the collection of signature images from various sources, such as user uploads or existing databases. This stage is crucial as it provides the foundational data for the entire system. Both genuine and forged signatures should be collected to ensure the model learns to differentiate between them effectively. The data must also include metadata, like user information and timestamps, for better context in analysis.

Data Preprocessing: Data preprocessing involves several steps to enhance the quality of the signature images before analysis. This includes image enhancement techniques such as noise reduction and contrast adjustment, followed by binarization, which converts the images to a black-and-white format. The goal is to prepare clean and uniform data, making it easier for the model to extract relevant features. Proper preprocessing is vital for achieving higher accuracy in subsequent steps.

Feature Extraction: In this stage, relevant features are extracted from the preprocessed signature images. This can include geometric features like height, width, and aspect ratio, as well as texture characteristics such as stroke width and curvature patterns. Feature extraction transforms the image data into numerical representations, which are essential for training machine learning models. High-quality features enable better model performance, leading to more accurate signature verification.

Model Training

Model training involves using the extracted features along with labeled data (genuine or forged) to teach the machine learning models. Various algorithms can be employed, such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), or Random Forest models, each contributing unique strengths to the training process. The models learn to identify patterns that distinguish genuine signatures from forged ones. Once trained, these models are evaluated for performance to ensure reliability.

Signature Verification

Once trained, the system can verify new signatures submitted by users. The incoming signature undergoes the same preprocessing steps, ensuring consistency with the training data. The preprocessed features are then fed into the trained models to generate predictions about the authenticity of the signature. The outcome typically indicates whether the signature is genuine or forged, providing users with immediate feedback.

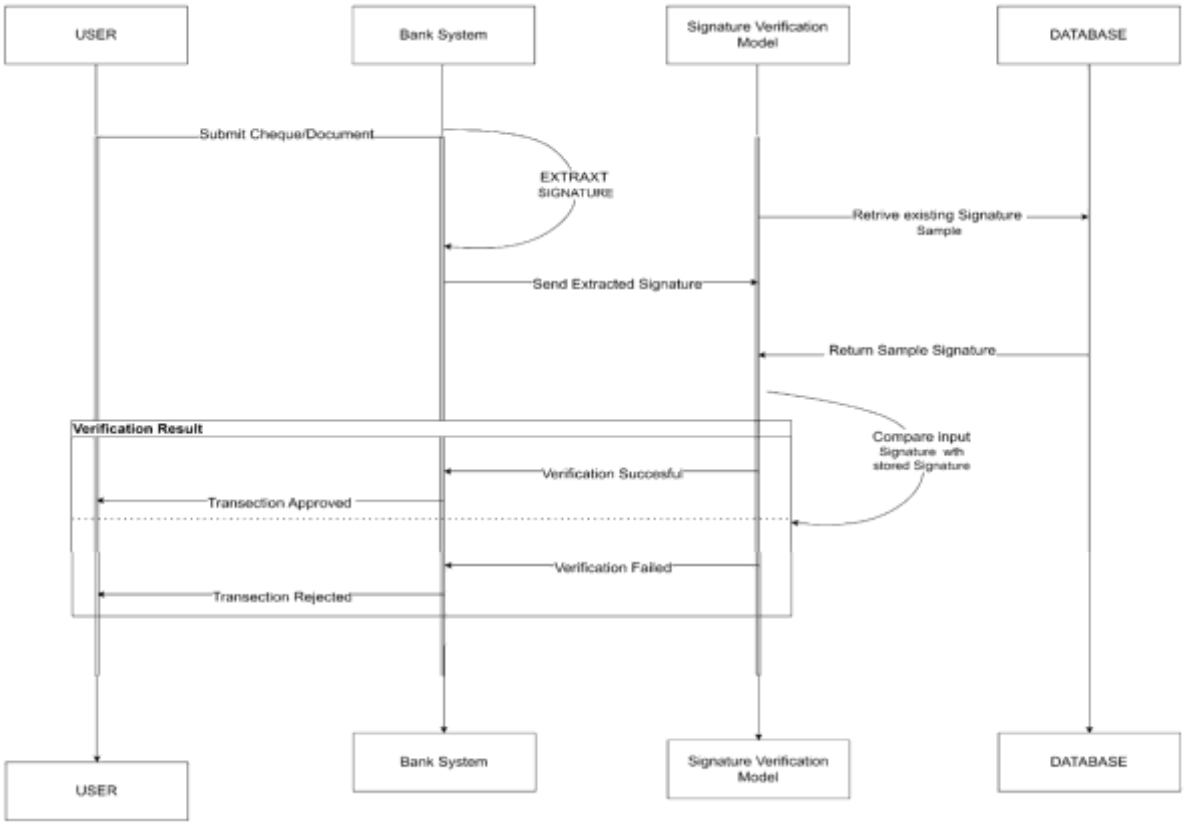
Results Visualization

The results of the verification process are presented through a user-friendly dashboard, allowing users to view predictions alongside relevant insights. This dashboard can include visualizations of feature importance, confidence scores, and user statistics for a comprehensive understanding of the verification outcomes. Effective visualization enhances user experience and helps in making informed decisions based on the system's predictions.

Deployment

The entire system is deployed as a real-time verification API, making it accessible for users to perform signature verification on demand. The API enables seamless integration with various applications, allowing for immediate processing of submitted signature images. By utilizing platforms like Flask and Heroku, the system can efficiently handle multiple requests while maintaining performance. This deployment ensures that organizations can utilize the signature verification capabilities in real-world scenarios, enhancing security and reducing fraud.

Sequence chart



Explanation:

1.User Initiates Request

A user uploads a signature image for verification through the user interface (UI), initiating the verification process.

2. Data Preprocessing

The UI sends the signature image to the Data Preprocessor, which enhances the image, binarizes it, and extracts relevant features to prepare the data for analysis.

3. Model Training

If no model exists, the pre-processed signature data is sent to the Model Trainer, where machine learning models are trained to distinguish between genuine and forged signatures.

4. Trained Model Transfer

Once trained, the model is transferred from the Model Trainer to the Predictor, ready for signature verification tasks.

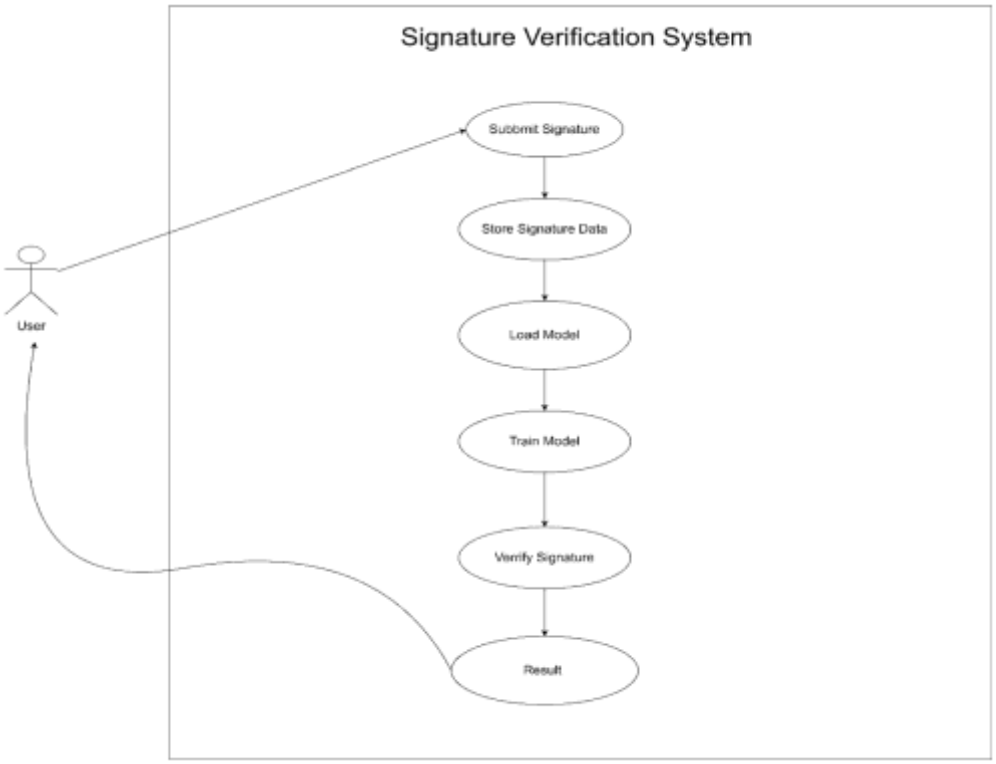
5. Signature Verification

The Predictor uses the trained model to analyze the submitted signature and predict its authenticity, returning the result to the UI.

6. Result Display

The prediction result, indicating whether the signature is genuine or forged, is displayed to the user in the UI, providing immediate feedback on the verification outcome.

Use case diagram



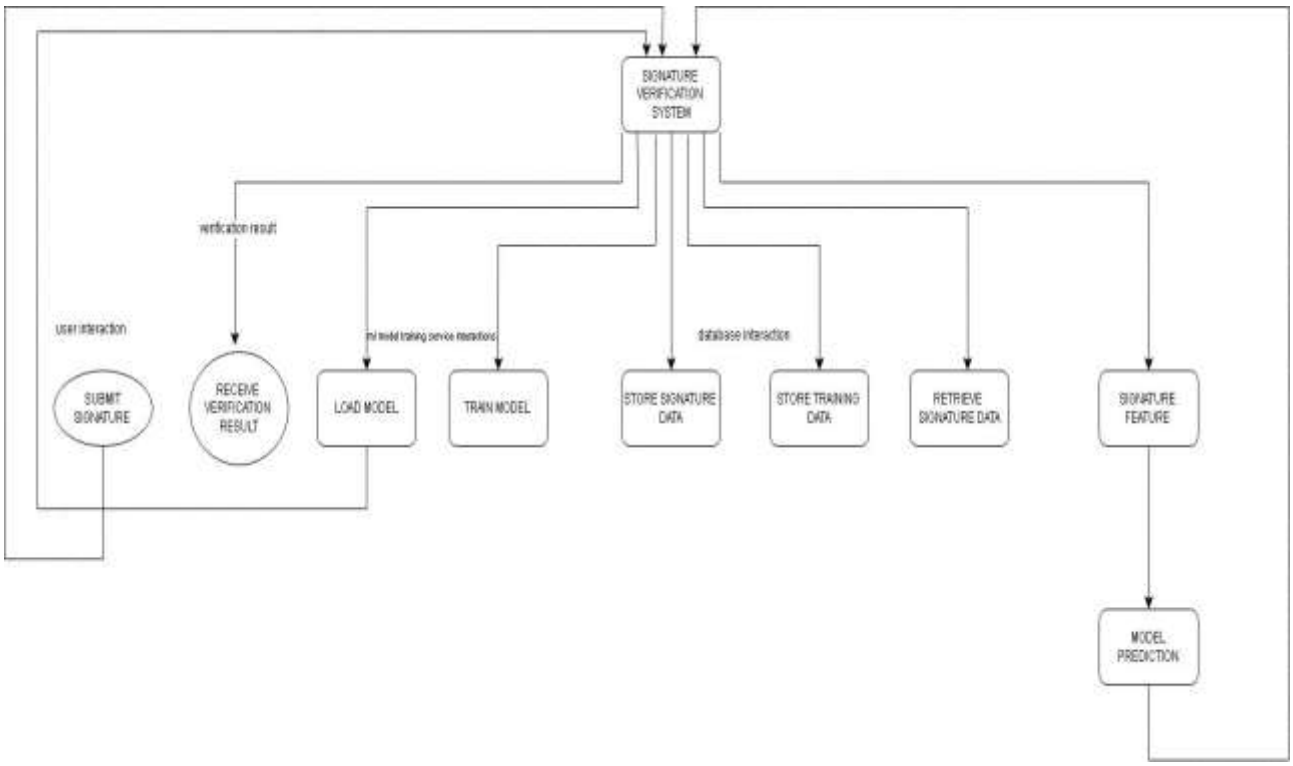
User Use Cases:

- Login: Users can log in to the user interface (UI) to access the system securely.
- Submit Signature: Users can upload a signature image for verification.
- View Verification Results: Users can view the results of the signature verification, indicating whether the signature is genuine or forged.
- Analyze Results: Users can analyze verification results and access additional insights about the signature's authenticity.

Developer Use Cases:

- Model Update/Modification: Developers can update or modify the machine learning model to improve accuracy or adapt to new signature patterns.
- System Maintenance: Developers can perform maintenance tasks to ensure the system runs smoothly and efficiently.
- Deploy Updates: Developers can deploy updated versions of the model and system features to enhance functionality.

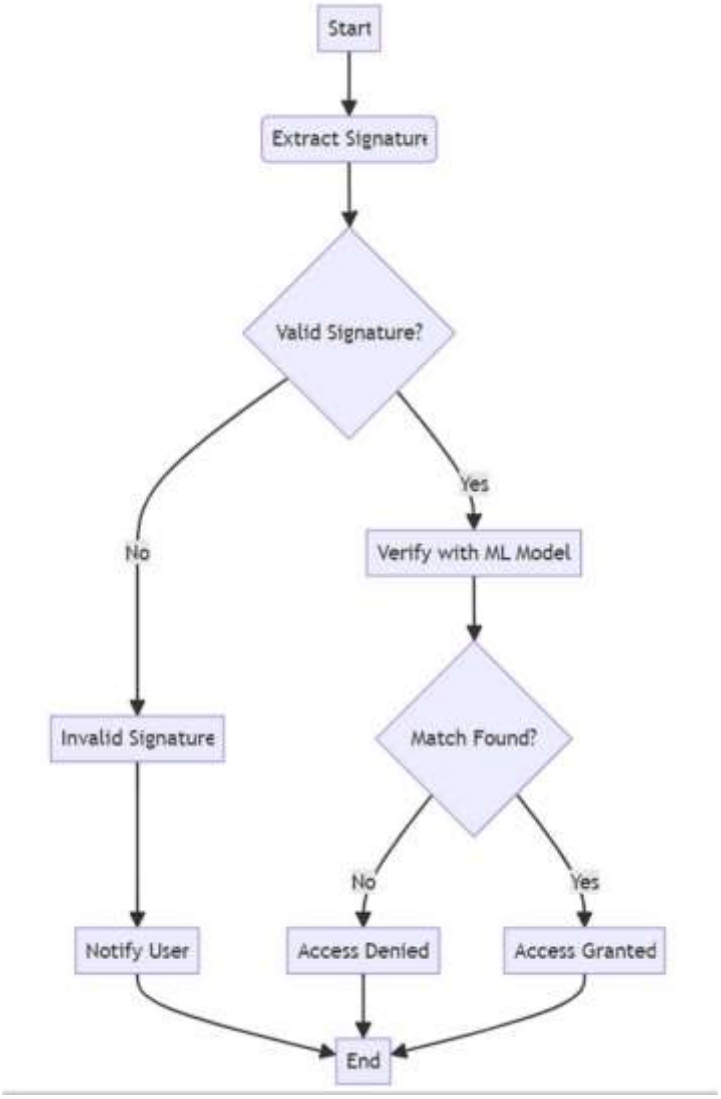
CONTEX DIAGRAM



The Signature Verification System for Reducing Financial Fraud follows a structured approach where multiple entities interact with the system to authenticate signatures on financial documents, such as cheques. The system's primary external entities include Users (Bank Staff or Customers), the Database, and the Bank's Internal System. The User uploads a cheque image, which is processed by the system. The OCR module extracts the signature, while the Line Sweep Algorithm isolates the signature region. The Machine Learning Model (SVM) then classifies the signature as genuine or forged based on trained data. Once verification is complete, the system returns the verification result to the user and updates the database with relevant records.

The Database stores user credentials, uploaded cheque images, extracted signatures, and verification results. If integrated with the Bank's Internal System, verified transactions can be approved or flagged for manual review in case of fraud suspicion. The Context Diagram visually represents these interactions, illustrating how data flows between users, the system, and external entities. This structured design ensures security, automation, and accuracy in fraud detection while enhancing operational efficiency in financial institutions.

Activity Diagram



The diagram is an activity diagram that visualizes the workflow of a Signature Verification System. Here's a brief breakdown:

1. Login: The user logs in by providing their credentials, and the system authenticates them.
2. Submit Signature: The authenticated user uploads a signature image for verification.
3. Signature Verification: The system processes the image and runs the verification model to determine if the signature is genuine or forged.
4. Result Display: The verification result (genuine or forged) is displayed to the user.

Cost Estimation And Effort Analysis

Introduction to Cost and Effort Analysis

Cost analysis and effort estimation are critical processes in project management that offer numerous benefits. By conducting a thorough cost analysis, organizations can gain a clear understanding of the financial resources required for a project, helping in budget allocation and avoiding unforeseen expenses. It ensures that the project remains financially viable and aligns with organizational goals. Effort estimation, on the other hand, helps in accurately predicting the amount of work and resources needed to complete tasks, aiding in realistic project scheduling and resource allocation. Together, they contribute to improved decision-making, better risk management, and enhanced project efficiency by minimizing the chances of overruns in both cost and time.

These processes ultimately enable better control and planning, leading to successful project completion within budget and deadlines.

Bottom-Up Cost Estimation for Making Model

The bottom-up cost estimation approach breaks down the project into smaller components and estimates the cost of each component separately. This method provides a more accurate cost estimate as it considers the specific requirements of each project element.

Detailed Cost Breakdown

Category	Description		Cost
1. Data Collection			
Data Sourcing	Use of open datasets (publicly available)	₹ 0	No cost if you rely on publicly available datasets, especially for a proof-of-concept.
2. Data Storage			
Local Storage (Hard Drive)	Storing data on local drives (up to 100GB)	₹ 0	Store data on personal or local machines, eliminating the need for cloud storage in the initial stages.
Data Management	Excel for local storage	₹ 0	Open-source databases like Excel can be used without any cost.
3. Software and Tools			
Python Installation	Programming language for model development	₹ 0	Python is open-source and free to use.
Data Libraries	Pandas, NumPy for data manipulation	₹ 0	These are open-source Python libraries widely used in data science projects.
Machine Learning Libraries	Scikit-learn, XGBoost	₹ 0	These libraries are open-source and freely available for machine learning purposes.
Integrated Development Environment (IDE)	VS Code and Jupyter Notebook	₹ 0	VS Code and Jupyter Notebooks are free, open-source tools for development.
Version Control	Git for version control and collaboration	₹ 150	Git is open-source and can be used with GitHub or GitLab's free tiers for project collaboration. Maintenance charges.
4. Model Training			

Local CPU Training	Training small datasets on local machines (CPU)	₹ 0	For small datasets, local machines can be used to run the model without requiring external servers.
5. Deployment			
Flask or Django Framework	For deploying the model as a web service or API	₹ 0	Flask and Django are open-source frameworks for deploying models and web applications. This will include in future scope
Local Server Deployment	Running the model locally during development	₹ 500	During development, you can run the model on a local server, such as your personal computer. If computer rent cost
6. Hardware			
Personal Computer/Laptop	Use existing personal hardware for development	₹ 200	Assuming no additional hardware purchases are needed if you have a reasonably powerful laptop or desktop. Except electricity.
7. Maintenance			
Model Updates	Periodic retraining with new data (on local system)	Negotiable	Perform regular updates locally to avoid cloud usage charges.
Bug Fixes and Enhancements	Handling software issues as required	Negotiable	No cost if maintenance and updates are handled by the development team.
8.Effort	Labour cost	₹ 10000	Standard value for project which can be about at given price .
9.Documentation			
Cost of documentation		₹ 1500	
Total		₹ 12350	

Note: The Project is built for academic purposes, and we are primarily using free and open-source resources.

Effort Estimation Using COCOMO II Model

The COCOMO II model uses a formula to calculate the Effort Adjustment Factor (EAF) based on various attributes of the Signature Verification project. Here's a simplified version of the formula:

EAF = (SF1 * SF2 * SF3 * SF4 * SF5) ^ 0.5

where:

- SF1: Product Attribute (PRODUCT_ATTR)
- SF2: Computer Hardware Attribute (COMPUTER_ATTR)
- SF3: Personnel Attribute (PERSONNEL_ATTR)
- SF4: Project Attribute (PROJECT_ATTR)
- SF5: Application Experience Attribute (APP_EXPER)

Each of these attributes has a scale of 1 to 5, where 1 represents the most favorable condition and 5 represents the least favorable condition.

To calculate the EAF for your Signature Verification project, you'll need to assess the values for each of these attributes.

For example, if you believe that your project involves:

- A moderate level of complexity in signature recognition (SF1=3),
- Requires advanced computational hardware (SF2=4),
- A team with considerable experience in machine learning (SF3=2),
- A medium-sized project scope (SF4=3),
- Your team has some experience with similar projects (SF5=2), your EAF would be calculated as follows:

1. Calculate EAF:

Using the given ratings for each cost driver, we can calculate the EAF:

EAF = 1.40 * 1.50 * 1.00 * 1.11 * 1.11 * 0.87 * 1.00 * 1.00 * 1.17 * 0.90 * 0.95*1.10 * 0.83 * 1.00 * 1.00

EAF ≈ 4.367

2. Calculate Adjusted Effort (EIntermediate):

Assuming the basic effort estimate (EBasic) is 2.676 person-months, we can calculate the adjusted effort as:

EIntermediate = EBasic * EAF = 2.676 * 4.367 ≈ 11.67 person-months

3. Calculate Adjusted Development Time (DIntermediate):

Using the formula

DIntermediate = c * (EIntermediate)^d, where c = 2.5 and d = 0.38, we get:

DIntermediate = 2.5 * (11.67)^0.38 ≈ 6.89 months

4. Calculate Adjusted People Required (PIntermediate):

Using the formula

PIntermediate = EIntermediate / DIntermediate, we get:

5. PIntermediate = 11.67 / 6.89 ≈ 1.69 (or effectively 2 people) Summary:

The calculated EAF is 4.367, indicating that the Signature Verification project is somewhat more challenging than a typical project.

The adjusted effort estimate is 11.67 person-months.

The adjusted development time is 6.89 months.

The adjusted people required is approximately 2 people.

Project Effort Distribution

Effort Distribution by Phase

Phase	Description	Percentage of Total Effort	Person-Months
Requirements Analysis	Understanding business needs, defining project scope	15%	1.75
Data Collection & Preprocessing	Gathering and preparing data for analysis	20%	2.33
Model Development	Feature engineering, model selection, training	30%	3.5
Testing & Validation	Evaluating model performance	15%	1.75
Implementation	Deploying the model in the target environment	10%	1.17
Documentation	Creating technical and user documentation	10%	1.17
Total		100%	11.67

Resource Allocation Timeline

Month	Primary Activities	Deliverables
Month 1	Requirements Analysis	Project scope document, requirements specification
Month 2	Data Collection & Preprocessing	Clean dataset, data dictionary
Month 3	Feature Engineering & Model Selection	Feature importance analysis, model selection report
Month 4	Model Training & Validation	Trained model, validation results
Month 5	Model Optimization & Testing	Optimized model, test results
Month 6-7	Implementation & Documentation	Deployed model, documentation

Cost-Benefit Analysis

Expected Benefits

Benefit Category	Description	Estimated Value (Annual)
Reduced Customer	5% reduction in customer rate	₹ 500,000
Improved Customer Targeting	More efficient marketing campaigns	₹ 200,000
Enhanced Customer Satisfaction	Through proactive customer service	₹ 150,000
Optimized Resource Allocation	Better allocation of customer service resources	₹ 100,000
Total Annual Benefits		₹ 950,000

Return of Investment (ROI)

Year	Annual Cost (₹)	Annual Benefit (₹)	Net Benefit (₹)	Cumulative Net Benefit (₹)
1	12,350	9,50,000	9,37,650	9,37,650
2	5,000	9,50,000	9,45,000	18,82,650
3	5,000	9,50,000	9,45,000	28,27,650

ROI (3-year) = (Total Benefits - Total Costs) / Total Costs = (2,850,000 - 22,350) / 22,350 ≈ 12,647%

The extremely high ROI indicates that the project is highly cost-effective, primarily due to the use of free and open-source resources and the significant potential benefits of reducing customer.

Risk Assessment and Contingency Planning

Cost-Related Risks

Risk	Probability	Impact	Mitigation Strategy	Contingency Budget (₹)
Increased complexity requiring more resources	Medium	High	Start with a simpler model and gradually increase complexity	5,000
Data quality issues requiring additional preprocessing	High	Medium	Allocate additional time for data cleaning	3,000
Need for cloud resources for larger datasets	Low	Medium	Plan for scalable infrastructure from the beginning	10,000
Total Contingency Budget				₹ 18,000

Schedule-Related Risks

Risk	Probability	Impact	Mitigation Strategy
Delays in data collection	Medium	High	Start with available data and expand later
Model performance below expectations	Medium	High	Allow time for multiple iterations
Integration issues with existing systems	High	Medium	Involve stakeholders early in the process

Summary of Cost and Effort Analysis

The cost and effort analysis for the signature verification model project reveals several key insights:

1. **Cost-Effectiveness**: The project is highly cost-effective, with a total estimated cost of ₹12,350, primarily due to the use of free and open-source resources.

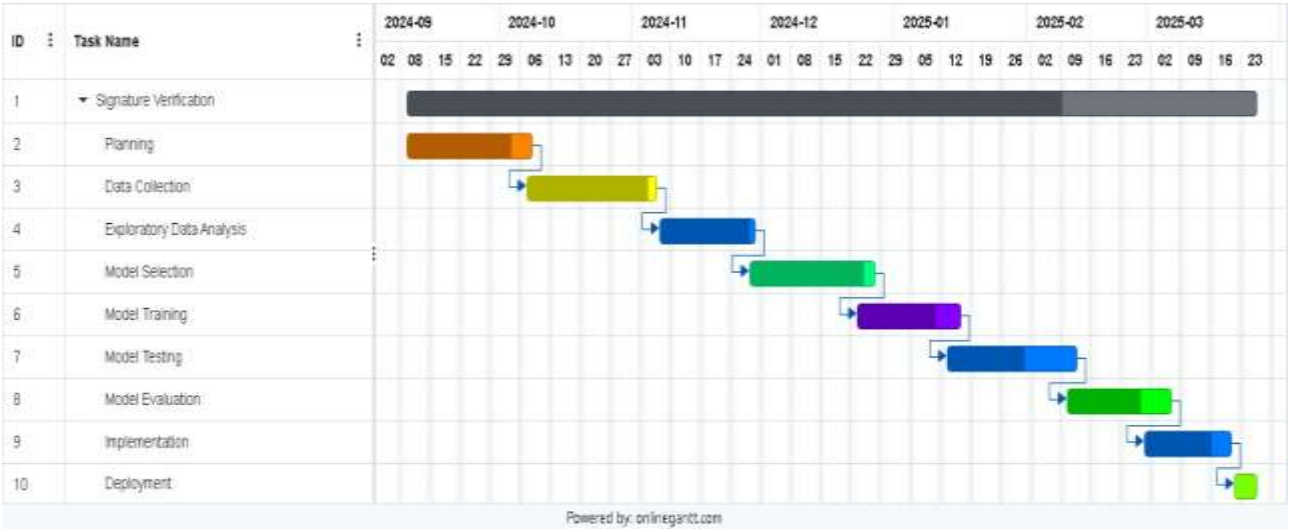
2. **Effort Estimation**: Using the COCOMO II model, we estimate that the project will require approximately 11.67 person-months of effort, with a development time of 6.89 months and a team of 2 people.

3. **Return on Investment**: The project has an extremely high ROI of approximately 12,647% over three years, indicating that it is a highly valuable investment.

4. **Risk Management**: We have identified several cost and schedule-related risks and have allocated a contingency budget of ₹18,000 to address these risks.

5. **Resource Allocation**: The project will require a team of 2 people,

GANTT CHART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1 Signature Verification
2 Planning
3 Data Collection
4 Exploratory Data Analysis
5 Model Selection
6 Model Training
7 Model Testing
8 Model Evaluation
9 Implementation
10 Deployment
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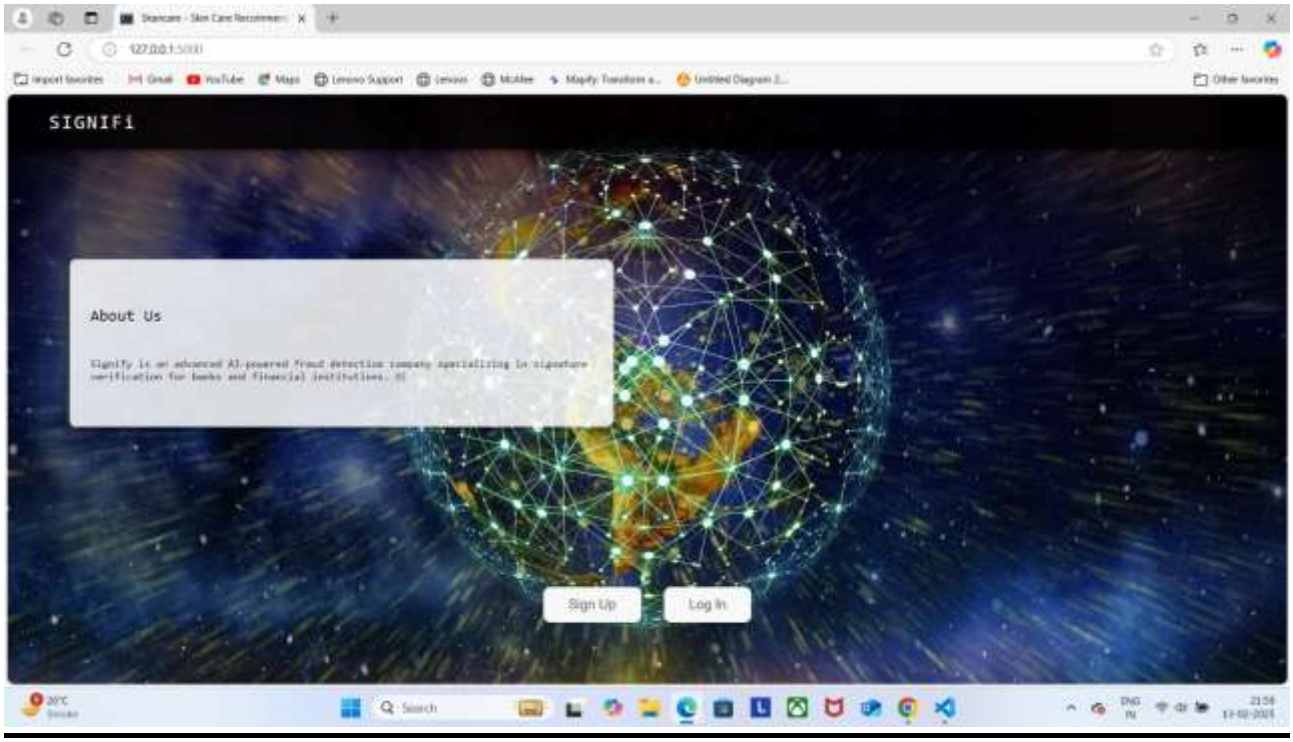
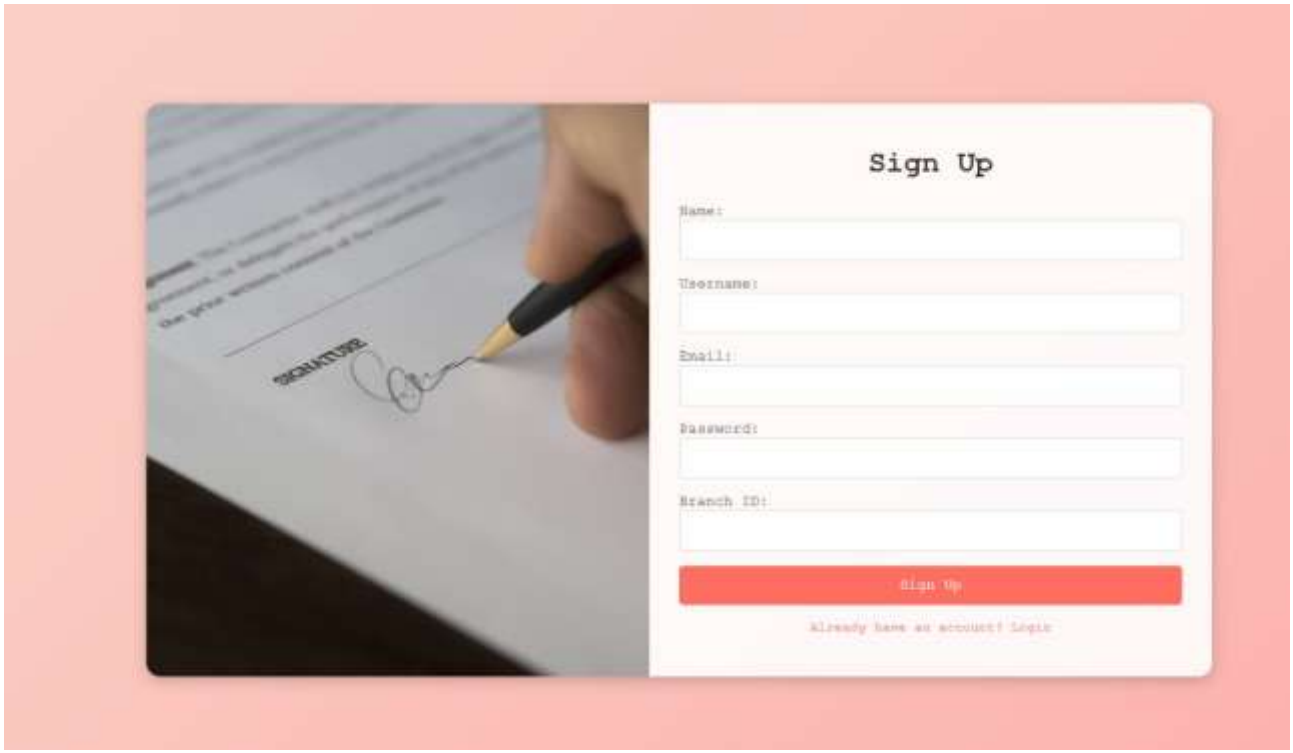
Implementation

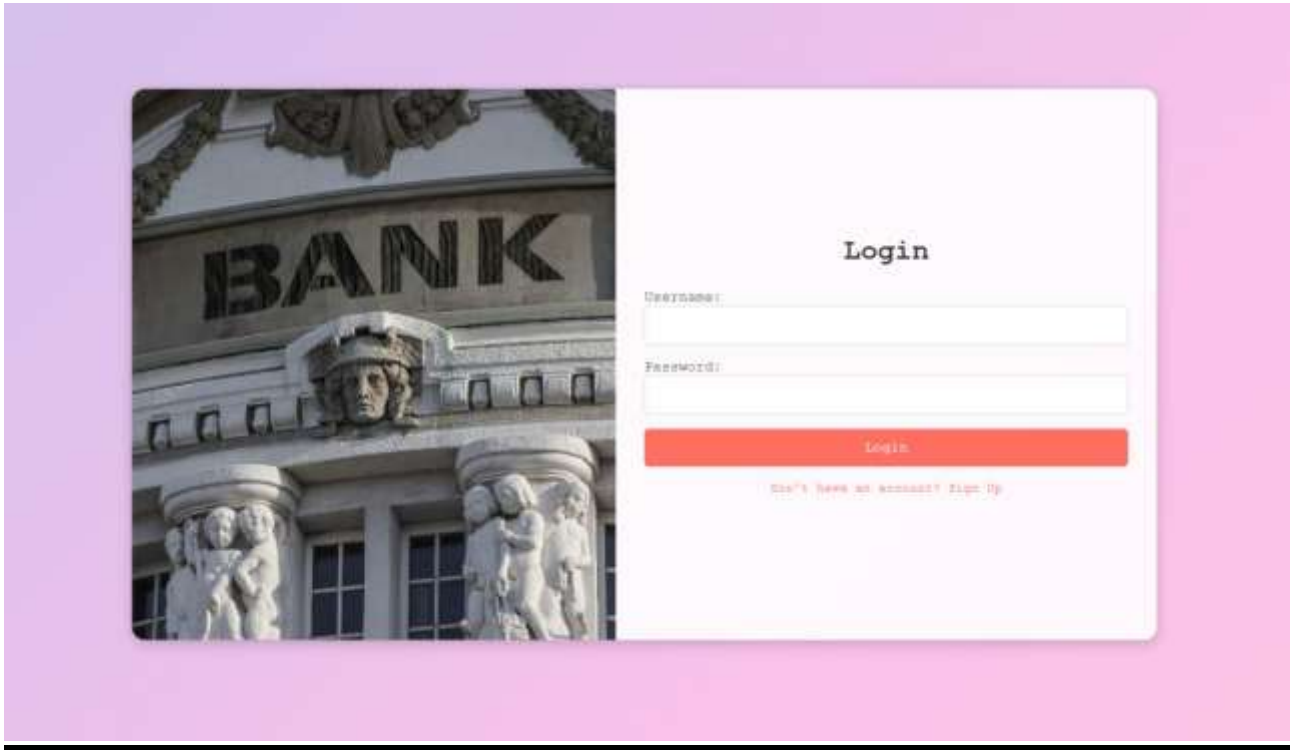
This is landing page of SigniFi : Signature Verification Using ML For Reducing Bank Fraud



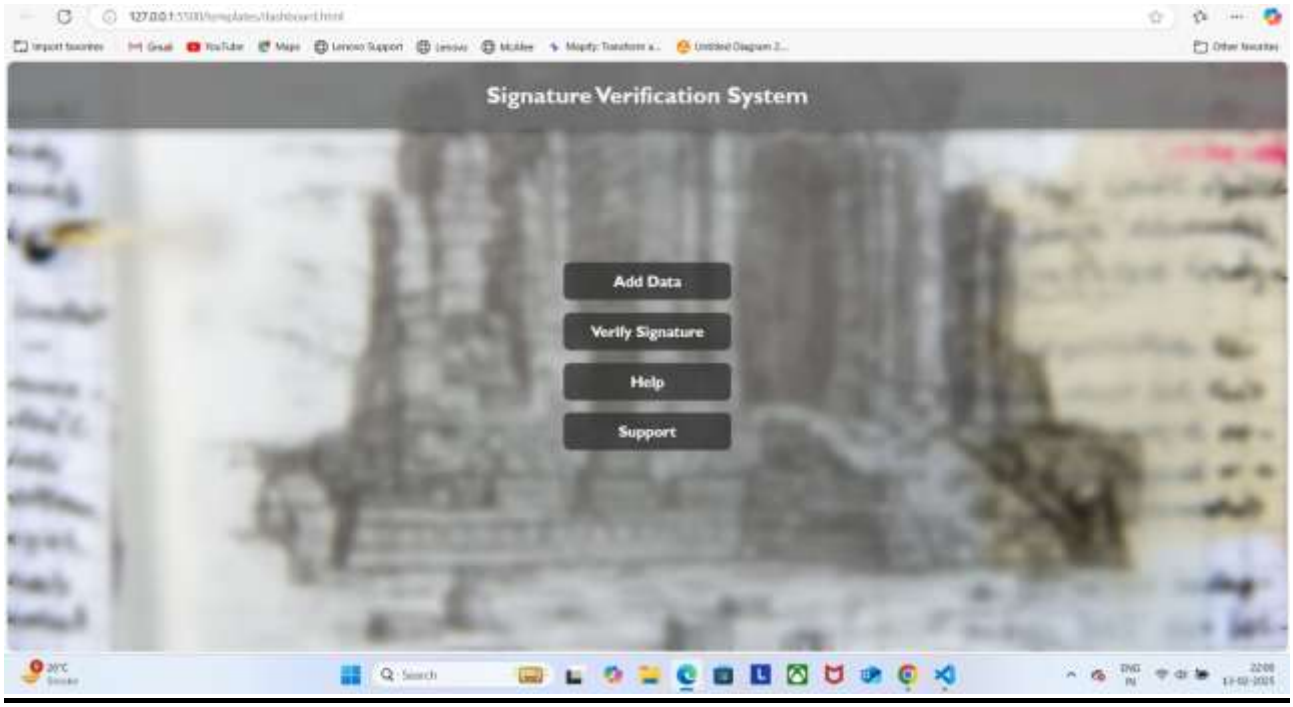
Sign-Up Page



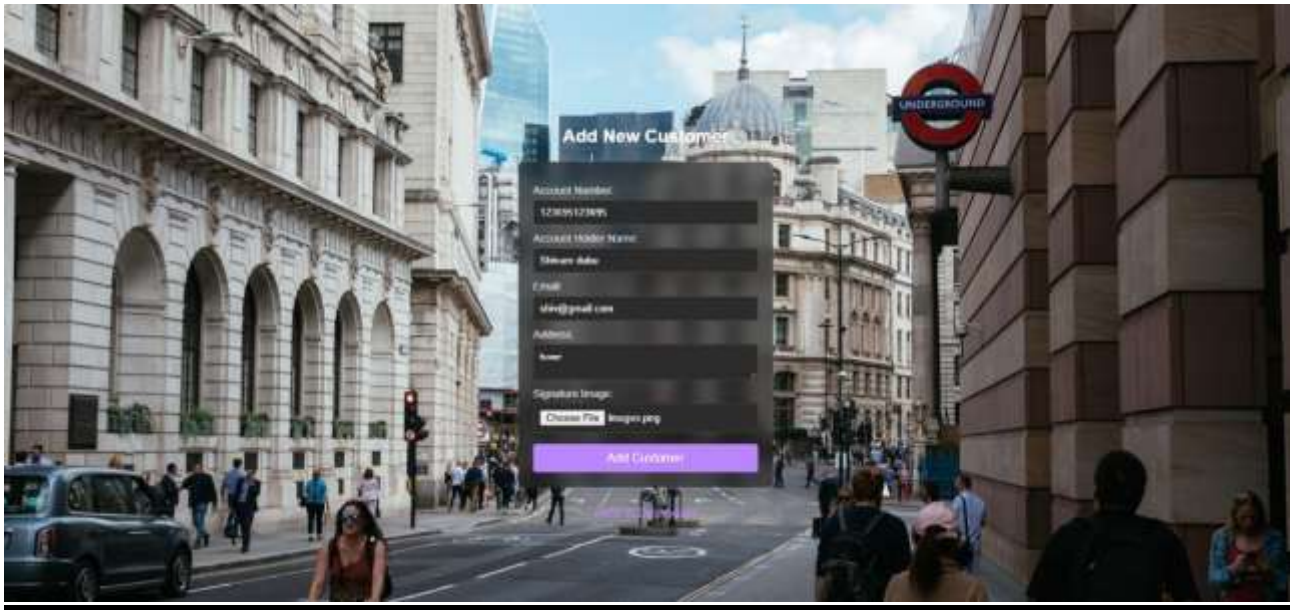
Login Page



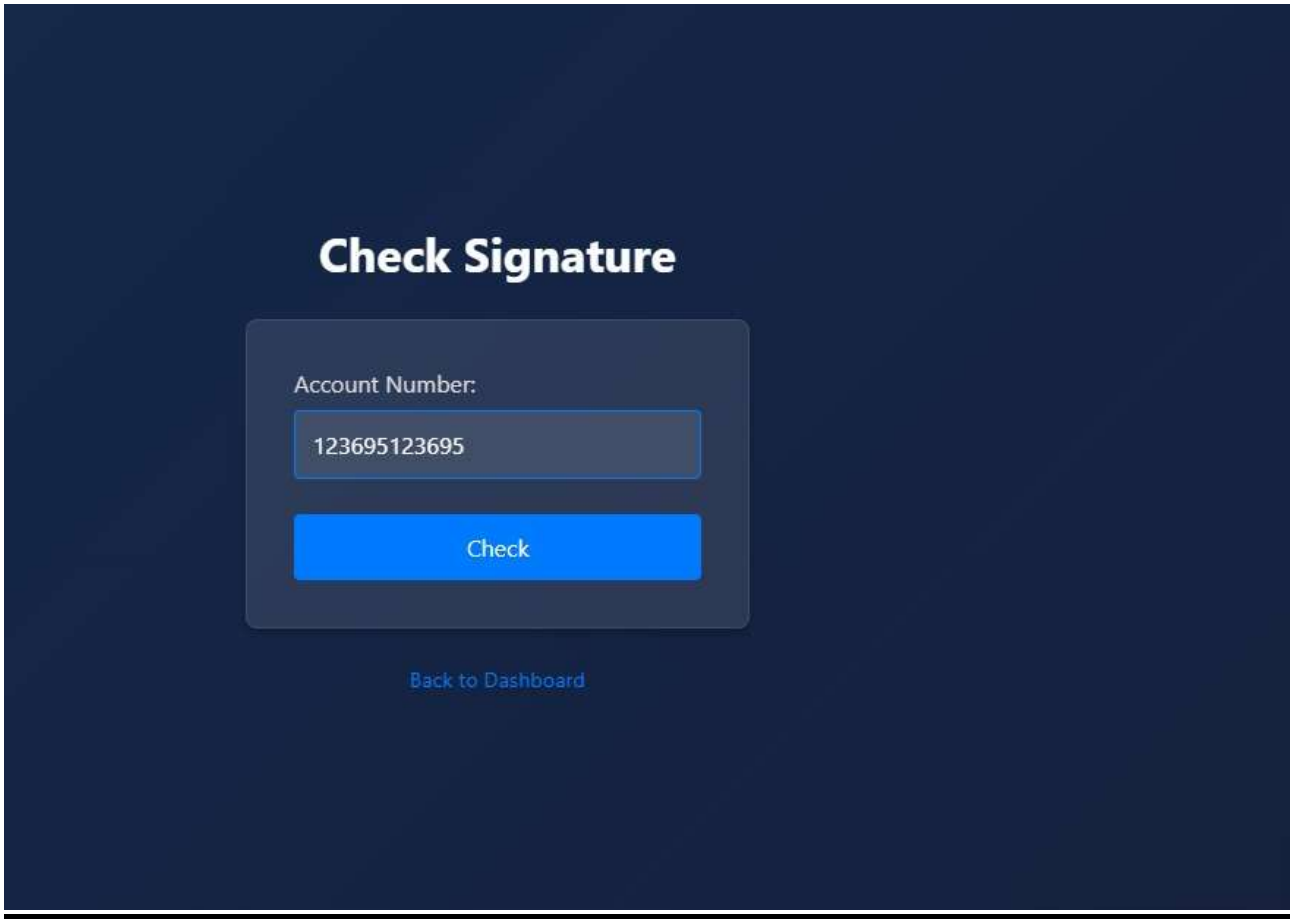
Home Page



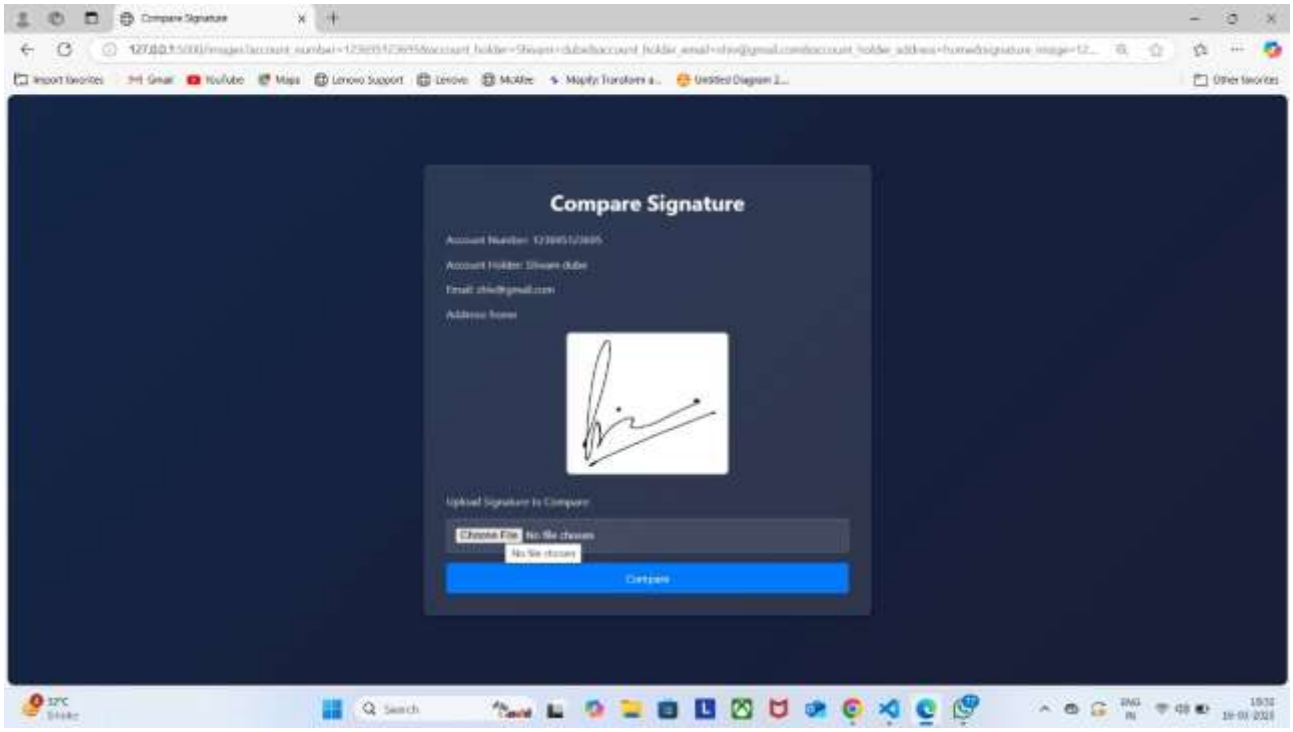
Add New Customer Data



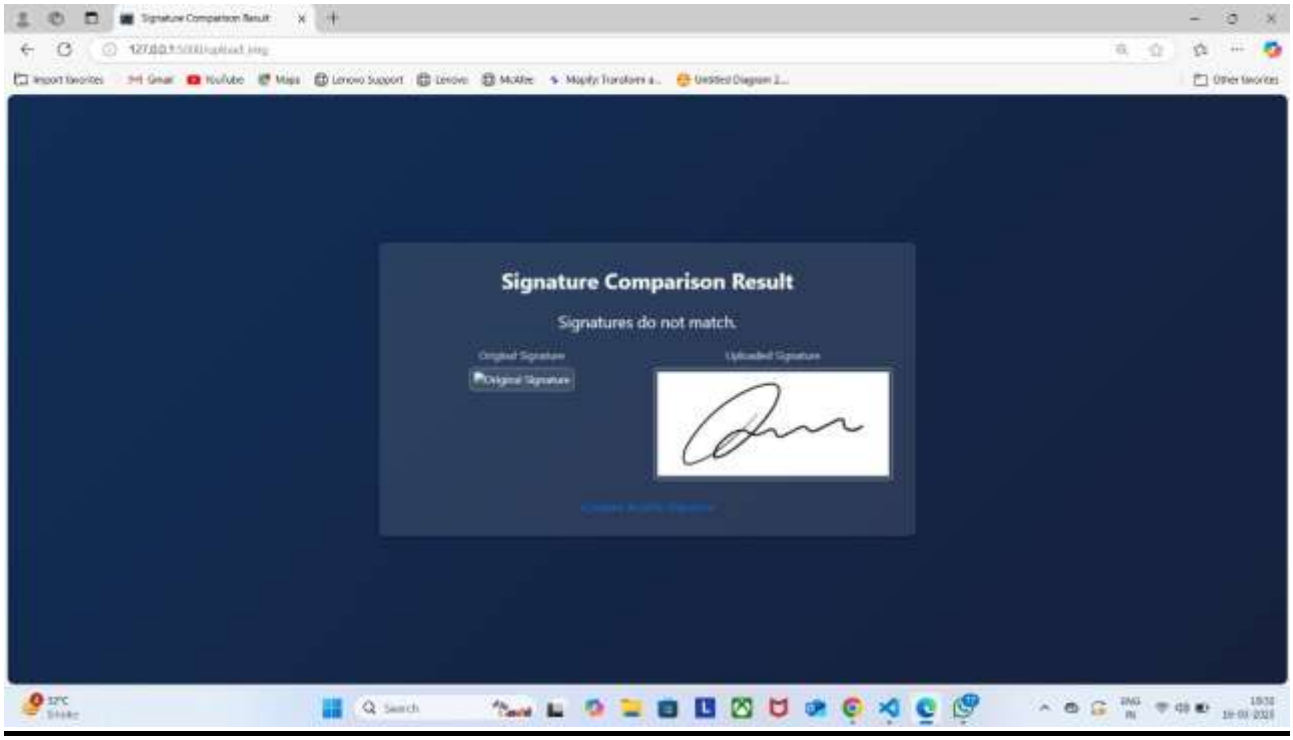
Verify Signature (Extracting Customer Data By Account Number)



Signature Comparison (Fetched User Data And Comparison)



Signature Verification Result



Future work

Future Work for Signature Verification System

1. Integration with Fraud Detection and Risk Assessment Systems:

- By integrating the signature verification system with broader fraud detection or risk assessment frameworks, financial institutions can better analyze transactions in real-time. The system can flag suspicious activities where forged signatures are detected and notify relevant teams for further investigation.
- Benefits:
  - Automated Risk Analysis: The system can automatically assess the likelihood of fraud based on signature authenticity, enabling quicker decision-making in high-risk cases.
  - Targeted Interventions: Allows financial institutions to focus resources on investigating transactions that pose higher risks, improving overall efficiency.

2. Improved User Interface and Enhanced Security:

- Enhancing the interface will ensure that users, including bank employees or analysts, can easily upload signatures, review results, and generate reports without technical difficulty. A user-friendly interface simplifies the system's use for non-technical stakeholders.
- Security Upgrades:
  - Implementing stronger security measures such as end-to-end encryption, multi-factor authentication (MFA), and strict access control policies will help in safeguarding sensitive signature data.
  - Compliance with legal frameworks like GDPR is crucial when dealing with personal or financial signatures.

3. Integration with Live Data for Real-Time Verification:

- Integrating live transaction data with the signature verification system ensures that signatures are verified in real-time. This capability would be particularly valuable in high-speed environments like digital banking, where fraudulent transactions need immediate detection.
- Benefits:
  - Real-Time Decision Making: The system can provide instant feedback on the authenticity of a signature, allowing organizations to approve or flag transactions quickly.
  - Dynamic Model Updates: The model can be continually updated as new signature data comes in, enhancing accuracy over time.

Continuous Learning and Model Monitoring:

- Implementing continuous learning mechanisms where the model can learn from new data (e.g., new signatures or confirmed fraud cases) will make the signature verification system more adaptable.

- Monitoring tools like Prometheus can be used to track both the model's performance and system health.
  - Model Performance: Monitoring key metrics like accuracy, false positives, and false negatives in real-time. Any decrease in performance (e.g., model drift) can be flagged for retraining.
  - System Health: Keeping an eye on infrastructure metrics such as CPU usage, memory, and database load to ensure that the system runs smoothly without failures or downtimes.

4. Advanced Model Techniques for Better Accuracy:

- Future versions of the system can leverage advanced machine learning techniques like deep learning models (e.g., GANs or LSTMs) to enhance the accuracy of signature verification, especially when dealing with subtle forgeries.
- Incorporating multiple forms of biometric analysis, such as handwriting dynamics, can also improve the system's ability to detect forgeries in complex or evolving cases.

5. Cross-Platform Integration and Scalability:

- Developing APIs to allow integration with other digital platforms or financial institutions' legacy systems can broaden the system's usability across different platforms.
- Scaling the system to handle a large number of concurrent transactions or signatures is crucial for broader deployment in industries like banking, insurance, or legal services.

Reference

Wikipedia - Signature Recognition

- This article on Wikipedia provides a general overview of signature recognition, both online and offline, along with various approaches using machine learning models.
- Signature Recognition - Wikipedia

Towards Data Science - Signature Verification using Deep Learning

- This blog post on *Towards Data Science* covers how deep learning techniques, especially Convolutional Neural Networks (CNNs), can be used for signature verification.
- Signature Verification using Deep Learning

Google Scholar - Automatic Signature Verification Machine Learning

- You can find many academic papers on Google Scholar that discuss signature verification techniques using machine learning, including CNNs, SVMs, and other models.
- Google Scholar - Signature Verification with Machine Learning

Medium - Signature Verification using Python

- A tutorial on *Medium* demonstrates how to implement a basic signature verification system using Python and machine learning libraries like Keras and TensorFlow.
- Signature Verification using Python