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Hybrid DL-ML Framework for Handwriting-Based Person Recognition

Nabaa Mohamed Alsamak[1] and Maysaloon Abed Qasim[2]
[1]Computer Engineering Department, Northern Technical University, Mosul, Iraq
[2]Technical Engineering College for Computer and Artificial Intelligence /Northern Technical University / Mosul / Iraq.
nabaa_alsamak5@ntu.edu.iq , maysloon.alhashim@ntu.edu.iq

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Corresponding author:
Name:Nabaa Mohamed Khalil
Affiliation: Northern Technical University
Email: nabaa_alsamak5@ntu.edu.iq

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A B S T R A C T

This work proposes an efficient handwriting-person-based identification scheme amalgamating deep learning and regular machine learning classifiers. 6,955 fine-quality Arabic handwriting samples were gathered from 107 users. Deep features were extracted using Convolutional Neural Networks (CNNs), and SVM, RF, and Logistic Regression (LR) were deployed for classification. The test accuracy of feature extraction with CNN was 99.92%, while CNN+SVM ٨ددreported a maximum classification accuracy of 99.95%, CNN+LR reported 98.90%, and CNN+RF exhibited 98.11%. The method has also been implemented as GUI program to facilitate user-uploaded writings-based real-time identification. Evaluation parameters such as accuracy, precision, recall, and F1-score confirm the effectiveness and robustness of the model. The findings confirm the potential of handwriting-based biometrics for secure identification and provide future directions for expanding to multilingual datasets and large-scale deployment.

1. Introduction

Identification of individuals through handwriting has been a valuable research field for decades, playing a significant role in different domains. While the recognition of faces is the most widespread type of individual identity utilized in banking and cybersecurity systems for verification, handwriting recognition is among the most advanced methods in this regard since it depends on the uniqueness of every individual. Just like fingerprints, every individual has his or her own unique style of handwriting that differentiates them from others. Handwriting uniqueness relies on several factors, like neurological and muscular structures, finger and hand movement, and the writing experience subject. Taking advantage of technology and artificial intelligence (AI), AI-powered systems have been suggested, leveraging AI platforms and deep learning algorithms in recognizing such handwriting patterns with high accuracy.

Recent developments in AI and deep learning have significantly improved the performance and accuracy of automatic handwriting recognition systems. Among the breakthroughs, Convolutional Neural Networks (CNNs) have shown excellent performance since they are able to learn high-level features from image data. By using multiple processing layers, CNNs are able to capture multiple levels of information and are therefore highly suited to tasks such as image classification, object detection, and handwriting recognition [1]. In this case, handwriting recognition in Arabic presents some challenges because of the cursive script, context-dependent form of characters, and diacritics. Addressing these challenges requires models capable of detecting both high-level structural features and fine local details. Despite these challenges, complex deep CNN architectures have achieved state-of-the-art performance on Arabic handwriting datasets, particularly in conjunction with preprocessing techniques such as normalization, denoising, and resizing [2].

Furthermore, the use of deep learning in biometric systems has been generalized from handwriting to DNA-based identification. An example of this is the Artificial DNA Algorithm for Recognition (ADAR), which achieved a 0% false acceptance rate (FAR) and false rejection rate (FRR) by examining patterns of nucleotides [3]. Similarly, for counterfeit detection, CNNs and other deep neural networks have achieved high accuracy—reaching 99.26%—in detecting visual patterns, demonstrating the robustness of CNNs on visual recognition tasks [4].

In this research, a CNN was trained to identify people from their handwriting. The most important aspect of CNNs is that they are able to extract high-level features from input images to identify complex visual patterns. It has various stages, which begin with the preprocessing of the original images, feature extraction, and then feeding the data through various convolutional layers to extract the distinctive handwriting traits of an individual. This paper thoroughly investigates the construction of a Convolutional Neural Network (CNN) and examines how the architectural design specifically the number of layers and their configuration directly affects the classification performance, with a particular focus on accuracy. Furthermore, it emphasizes the essential role of image preprocessing in the initial phase, demonstrating how effective preprocessing significantly enhances model evaluation and contributes to achieving high overall performance. The proposed CNN model is rigorously evaluated using various performance metrics, including accuracy and error rate, to ensure a comprehensive assessment of its efficiency and reliability.

In identity verification and security, handwriting recognition powered by AI has emerged as a solid method to identify an individual. Strong and secure verification systems have been developed to effectively verify user identities and prevent fraud.

Nevertheless, most current research only employs CNNs as end-to-end classifiers, which can result in limitations in generalization for use with large-scale handwriting databases or very similar handwriting styles. The research gap is in not having hybrid frameworks whereby CNNs for strong feature extraction are combined with conventional machine learning (ML) classifiers for more discriminative decision-making. To solve this issue, this research puts forward a hybrid CNN-ML framework whereby CNNs' strength in extracting deep handwriting features is exploited and combined with machine learning algorithms like SVM, Random Forest, and KNN for improved classification accuracy and lower error rates. The research novelty is in proving that a hybrid deep-machine learning method can perform better compared to CNN-only approaches in handwriting-person identification-based applications, thus delivering a more resilient and scalable identity verification and security applications solution.

2. Literature Review

Interesting related handwritten recognition studies can be chronologically reviewed as follows: Handwriting-oriented recognition is a major research area in biometrics based on the uniqueness of a person in their handwriting style. Previous works have attempted several biometric modalities, including fingerprints, faces, irises, and ears. However, handwriting is still a notoriously hard modality because it is heavily dependent on neurological, muscular, and behavioral aspects as well as having a large amount of intra-class variation. There are recent developments in deep learning technologies for CNNs, which increasingly enhance accuracy in recognition for these modalities. The literature is structured in a thematic manner in order to bring out achievements and shortcomings, as well as research deficiencies.

1. Fingerprint recognition using CNN

Fingerprint recognition has been heavily researched, with CNNs enhancing liveness detection and identification accuracy. Nogueira et al. (2015) introduced a CNN-based method for distinguishing real and simulated fingerprints on the LivDet 2009 and 2011 databases with 98.5% and 97.1% accuracy, respectively [5]. This research proved CNNs effective in feature learning and detection of spoofing. Dakhil and Ibrahim (2018) presented an end-to-end fingerprint identification system consisting of a combination of preprocessing, lightweight neural networks, and KNN classification with 93.97% accuracy [6]. Both research papers indicate superior performance, but their use of modality-specific features restricts generalization to other modalities, like handwriting.

2. Facial recognition using CNN

Face recognition has been significantly enhanced by deep learning. Zulfiqar et al. (2019) validated five pre-trained CNN classifiers for feature extraction and classification and found SqueezeNet yielded 98.76% accuracy using a 9,000-image dataset [7]. Prasetyo and Naufal (2020) created a bespoke CNN for extracting facial features with 96% accuracy [8]. Additionally, Hung (2021) introduced a hybrid HOG-CNN model incorporating HOG-feature-based detection combined with CNN embeddings for enhanced robustness in multiple datasets [9]. Hangaragi et al. (2023) improved recognition in harsh conditions based on Face Mesh landmarks incorporating DNN classification with 94.23% accuracy [10]. These works show CNNs are effective at extracting high-level features but mostly apply to facial information with no consideration for handwriting's distinctive variability.

3. Eye recognition and multimodal biometric systems

Albadrasawi et al. (2025) paid attention to male and female eye image classification based on CNNs with standard ML baselines (Random Forest, KNN, SVM), with 95% validation accuracy [11]. Geethika et al. (2025) introduced a multimodal face-iris-finger vein biometrics system using feature-level fusion for increased robustness, with over 98% recognition accuracy [12]. As multimodal schemes increase security and dependability, their collection is intricate and not specific for handwriting.

Synthesis and Research Gap Although CNNs showed exceptional performance in some biometric modalities, handwriting recognition is distinctive in having high intra-class variations, cursive script, and person-specific neuromuscular dependency. State-of-the-art CNN-only-based systems don't learn fine-grained handwriting features or generalize for a multi-writer environment. Furthermore, hybrid approaches involving CNN feature extractions with classic machine learning classifiers (e.g., SVM, Random Forest) for handwriting recognition are not thoroughly explored. Consequently, in our research, a hybrid CNN-ML-based framework for handwriting-person identification is introduced for leveraging CNN for a high level of feature extraction while exploiting ML classifiers for improving classification robustness as well as accuracy, with a focus on overcoming limitations encountered in prior works.

3. Proposed Methodology

The system worked out in the current study identifies the identity of the writer through the use of samples from writings, machine learning, and deep learning methods. The overall architecture is illustrated in Fig. 1, showing the consecutive processes from raw handwriting samples to final writer identification.

The system converts handwritten samples into digital data, applies preprocessing, extracts discriminative features using a CNN, and classifies the writer using either an external machine learning classifier (SVM, Random Forest, or logistic regression) or the SoftMax layer of the CNN.

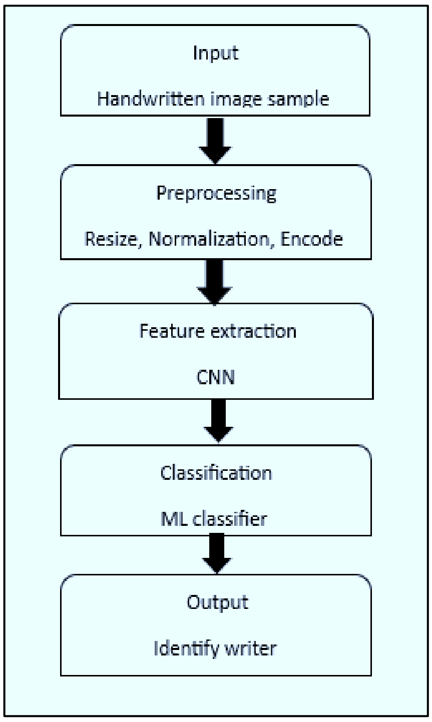

Fig. 1. Phased structure of the handwriting-based writer classification system.

3.1. Datasets

In order to develop good and diverse handwritten based identification system, a special dataset was compiled for this study. Data was collected through a good drawing tool, the XP-Pen Artist 12 (2nd Gen) Pen Display Tablet, to obtain good handwriting samples and avert issues like image noise, shadows, or distortion that usually occur whenever data is captured from paper.

107 individuals volunteered to assist with data collection. They came from various ages, genders, and educational levels to create a diversity of handwriting styles and to demonstrate true differences that occur in real life. Five different sentences of standard modern Arabic language were requested from the participants to write down. Fig. 2 shows sample images collected from individuals in the dataset.

Each individual wrote every sentence 13 times, thus contributing 65 handwriting samples to the dataset. This repetition also illustrates the variation in the way individuals write. In total, the dataset contains 6,955 images, all of them are in PNG format and of high quality. The study adhered to ethical standards by ensuring that every participant voluntarily agreed to contribute and signed informed consent.

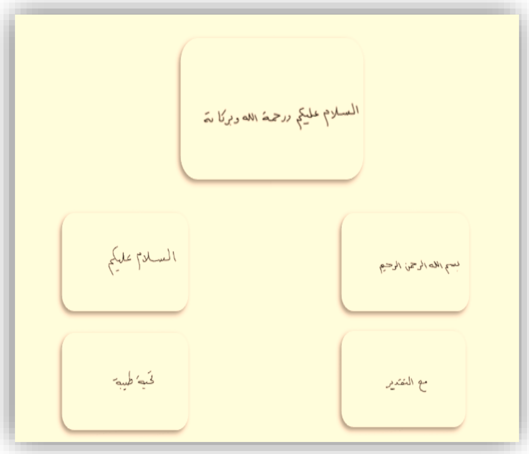

Fig. 2. Sample images from the handwritten dataset.

Also normalized all handwritten image pictures to 150 × 150 pixel size. Equal-sized images assured compatibility with the input size requirement of the CNN-based model and ensured equal processing at training time. Apart from input normalization, pixel values were normalized to the [0, 1] range by dividing by 255. Normalization must be performed to enable stabilization of training and to speed up convergent behavior because it restricts input features to some narrow range of constant numerical value.

In aid of multi-class classification, where a single class represents a given writer, the category labels were transformed to one-hot encoded vectors. With this representation, the model can generate a probability distributed across all of its classes and be trainable using respective loss functions. Data also were organized within a hierarchical directory structure where each subdirectory represented a distinct class (writer). That aided effective data loadng and automatic labeling from high-level data generators.

In order to sustain the fine-grained characteristics of handwritten letters, i.e., stroke width, curvature, and pressure behavior, all of the images were saved in PNG format, which is unrelated to lossy compression artifacts common to JPEG. These fine-grained characteristics hold crucial roles in precise feature extraction and writer identification.

Overall, every preprocessing step maintained the handwriting data in the normalized, cleaned, and optimal form to be trained for CNN, thus adding to the high degree of accuracy of classification and to the reliability of the model to classify different writers. Fig. 3 Illustrates steps including resizing, normalization, label encoding, and data organization.

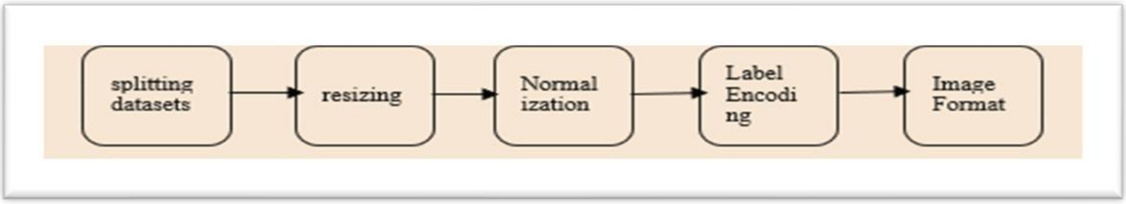

Fig. 3. The steps of preprocessing proccess.

3.3. Feature extraction using deep learning

Feature extraction in this study was performed through the convolutional neural network algorithm, which automatically learned discriminative handwriting features a series of convolutional and pooling layers that learned and extracted the most discriminate handwriting image features in a way that was automatic. Specifically, the model utilized the combination of the following: three convolution layers of sizes 32, 32, and 64, along with the down-sampling max-pooling layers following each convolution to reduce spatial dimensions and retain prominent features like stroke direction, edge contours, and curvature. ReLU activation to introduce non-linearity and model complex feature hierarchies.

After extracting the feature maps, the network proceeded to the classification step. The final pooling layer was flattened to a single-dimensional vector to be fed to dense (fully connected) layers. A dense layer with 512 units was included to learn the interaction and the high-level pattern of the extracted features. As preprocessing against the possibilities of overfitting and to promote generalization, dropout with the described rate of 30% was included, randomly dropping the neurons at the time of training. Finally, classification was done through the SoftMax output layer, producing a probability distribution over all the classes of writers to allow the model identify the most likely writer of a handwriting sample. Training was done using the categorical cross-entropy loss function for fitting a model to a multi-class classification task, and the model was trained with the Adam optimizer for stable, efficient learning at a low learning rate of 0.001.

3.4. Classification using machine learning algorithms

To be able to efficiently identify handwritten data, different machine learning classifiers were compared and tested. Machine learning classification involves learning a decision function from labeled data so that it can predict the class of unseen samples. There are different classifiers, all of which have some hyperparameters that significantly influence their learning and performance behavior. To be able to give a good and just comparison of chosen classifiers, parameter values were chosen wisely by following best practices

Support Vector Machine (SVMFor linearly separable spaces of features and linear classification, the linear kernel (kernel='linear') was employed for high-dimensional CNN features. In order to favor the larger margin separator more and to penalize the complexity of the model more severely, the regularization parameter C has been set to 0.01 to aid in the prevention of overfitting.

Random Forest (RF): For the sake of reducing computation and monitoring classifier behavior with exceedingly tiny tree populations, the ensemble model was initiated with a relatively modest amount of decision trees (n_estimators=5). For the sake of run-to-run reproducibility, the fixed random seed (random_state=42) was used.

Logistic Regression (LR): For appropriate optimization, for high-dimensional spaces of features or spaces where the speed of convergence is lower, the model convergence iteration count was set to max_iter=10. The default solver is okay unless approaches for multi-classes must be used.

These parameter choices for the classifier evaluation framework derived from the features extracted by the CNN achieve a good compromise between the accuracy, generalization, and these parameters have been chosen to enhance the performance across these dimensions. Table 1 illustrates a summary of the parameters used for each classification algorithm.

Table 1. Machine Learning Training Parameters.

Classifier	Key Parameters Used	Description
SVM	kernel='linear', C=0.01	Linear kernel with small C to increase margin and reduce overfitting.
RF	n_estimators=5, random_state=42	Small number of trees to reduce complexity and fixed seed for reproducibility
LR	max_iter=1000	Increased iteration cap to ensure convergence during optimization

3.5. Evaluation metrics for classification process

The performance of the machine learning algorithms was carried out on their respective test sets using different measures [13]:

- Accuracy

It refers to the ratio of occurrences correctly detected out of the total instances available. This measure is calculated by equation (1).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where, TP (True Positive) and TN (True Negative) represent the correctly predicted positive cases.

- Precision

This measure is the ratio of predictions that correct positive to the total of predictions that positive made. As in equation (2)[14]:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

- Sensitivity

It is the ability of model to predict actual positives. It is the ratio of correct positives to the total actual positives as shown in equation (3) [14]

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

- *F1-Score*

In cases where a dataset is unbalanced, F1-Score summarizes the trade-off among precision and recall. It's the harmonic mean of both of these metrics. It is calculated as equation (4) [14]

$$F1\_Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (4)$$

4. Results

The model was performed on a locally available computer with mid-specifications, an Intel Core i7-6600U processor, 8 GB of RAM, and a Windows 10 (64-bit) operating system. No graphics processing unit was used, and the CPU was used for training. The model was developed using Python version 3.10 and the TensorFlow 2.x, Keras, and Scikit-learn libra CVH Bries. The data was split into 70% for training, 20% for validation, and 10% for testing, with the images resized to 150 x 150 pixels and normalized.

❖ CNN result

CNN, in this work, was employed as the feature extractor with the functionality of discriminating writing behavior. Fig. 4 indicate the accuracy and loss curves with the employment of 15 epochs in an attempt to explain the monitoring of the training of the CNN model. The model is able to extract very informative features, as seen from the curves of leanings, with the validation accuracy attaining 99.92%, the training accuracy attaining 98.64%, and the test accuracy 99.92%, Additionally, the loss test set corresponding loss values show a noticeable decline to 0.0045, indicating that the feature extractor is convergent and stable. With precision, recall, and F1-score all equal to 99.94%, evaluation metrics validated this exceptional performance. The reliability and efficiency of this setup are demonstrated by such steady and nearly flawless scores.

Computationally, the model was of moderate complexity with about 9.55 million trainable parameters and used around 32 minutes of training time for 15 epochs using CPU. Average prediction time was 208 ms per image, which is permissible when utilized for research purposes but will have to be optimized when actualized in real time. This type of steady, nearly perfect score confirms the strength and consistency of the proposed setup.

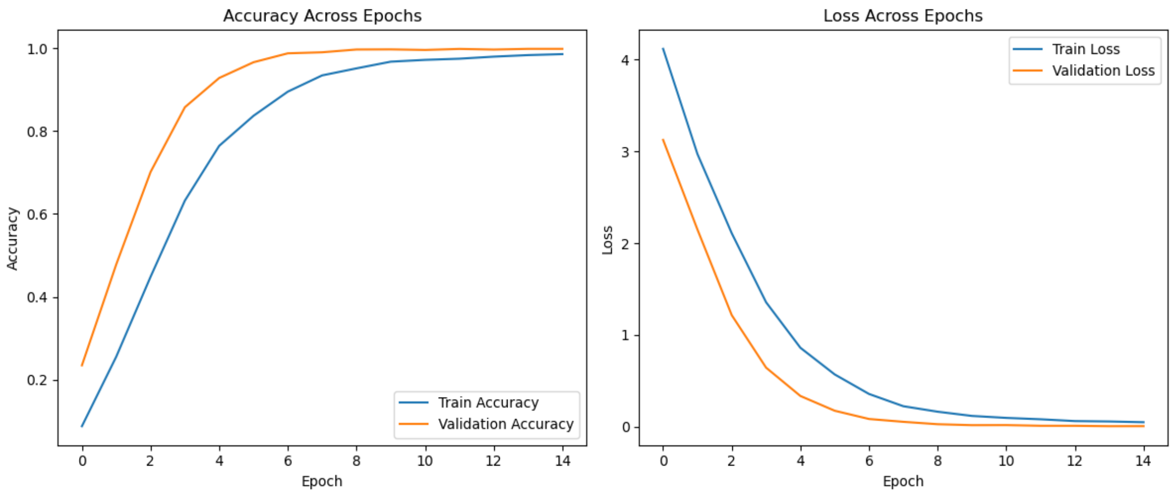

Fig. 4. Train and Validation Accuracy for CNN.

❖ ML results

This section contains the results of applying different machine learning algorithms to the dataset. The evaluation of each model is performed using performance metrics, including accuracy, precision, recall, and f1 score for each algorithm (SVM, RF, LR) used in this study.

❖ SVM results

Using deep feature representations taken from CNN, the classification performance of the SVM was thoroughly evaluated in this study. A one-vs-rest (OvR) approach was used to address the multi-class classification problem with 107 distinct identity classes. Converting the multi-class problem into a sequence of binary classification tasks, this method enables SVM to independently create the best decision boundaries for every class.

The learning curves reveal consistent training behavior, with both training and validation accuracies that reach 96.82% and 98.68%, respectively, steadily improving over the epochs. Loss values decreased significantly, confirming efficient learning dynamics and reduced generalization error. Fig. 5 obtain the train and validation for SVM.

The SVM classifier obtained an outstanding test accuracy of 99.95%, according to the final evaluation results. A precision of 99.95%, recall of 99.95%, and F1-score of 99.95% were also achieved by the model, demonstrating not only its high classification accuracy but also its balanced performance across all evaluation metrics. The robustness is strengthened by this consistency across various performance metrics.

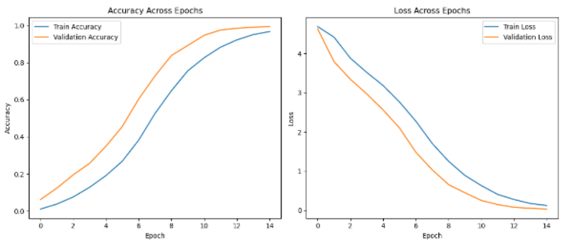

Fig. 5. Train and validation for SVM.

SVM works well in this situation because it can create distinct, high-margin decision boundaries in a feature space that has been transformed, particularly when paired with kernel functions that allow for nonlinear separation. For practical applications in identity verification and security systems, this combination of CNN-based feature extraction and SVM classification offers a strong framework for handwriting-based biometric identification with high precision, scalability, and reliability.

❖ RF result

RF algorithm was used as a classifier to assess the discriminative power of the features that were extracted using the CNN model. The accuracy and loss curves showed steady and increasing learning over 15 epochs during the training phase. The training accuracy closely followed, reaching 97.35%, while the validation accuracy increased steadily, reaching 99.81%. This convergence shows that the deep features that were extracted were well-separated in the feature space, highly representative, and effectively learnable. Fig. 6show the the train and validation for RF.

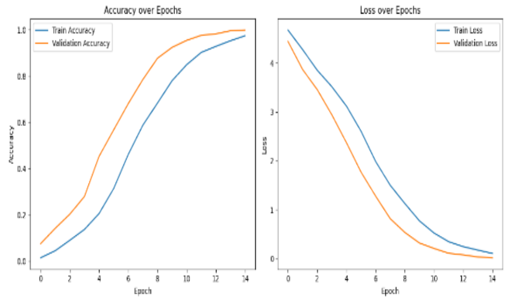

Fig. 6. Train and validation for RF.

The performance of the RF classifier on the test dataset provided additional evidence of the resilience of the system. With a precision of 98.17%, a recall of 98.11%, and an F1-score of 98.11%, the test accuracy of the model was 98.11%.

These findings demonstrate a well-balanced and effective classification model that can effectively generalize to handwritten samples that have not been seen.

All things considered, the high test and validation metrics demonstrate how well CNN-based feature extraction and RF classifiers work together for handwriting-based person recognition. Strong test results and consistency between training and validation trends imply that the model is not only accurate but also stable and dependable for practical uses.

❖ LR result

This method sought to determine whether the expressive potential of deep features could be used to achieve accurate classification with a comparatively simple linear classifier. The model was successfully learning the underlying patterns in the feature space, as evidenced by the steady and constant upward trend of the training and validation accuracy curves over the training epochs.

The training and validation loss values also sharply declined at the same time, indicating steady and seamless model convergence. In the last epoch, the training and validation accuracy of the model were 96.62% and 99.17%, respectively, indicating a high capacity for generalization and little overfitting. Fig. 7 explain the train and validation for LR.

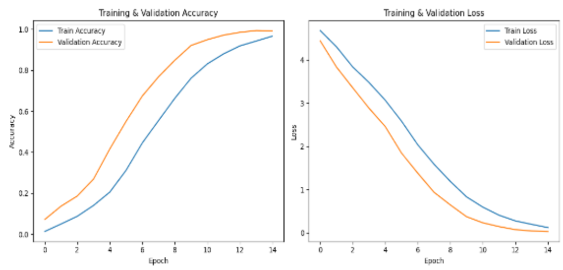

Fig. 7. Train and validation for LR.

The LR classifier achieved 98.89% test accuracy and produced flawless classification results when used on the test dataset. Additionally, the evaluation metrics were equally impressive, showing perfect performance in correctly predicting each class, with precision, recall, and F1-score all reaching 98.90%.

Table 2. Summary of ML parameters results.

Classifier	Train Accuracy	Validation Accuracy	Test Accuracy	Precision	Recall	F1-Score
SVM	96.76%	99.11%	99.95%	99.95%	99.95%	99.95%
RF	97.35%.	99.81%	98.11%	98.17%	98.11%	98.11%
LR	96.62%	99.17%	98.89%	98.9%	98.9%	98.9%

These findings highlight the benefits of integrating a multinomial SVM classifier with CNN-based feature extraction, demonstrating that even basic models can attain exceptional accuracy when constructed using deep features that are rich and well-structured.

❖ Proposed handwritten system

In order to provide a user-friendly handwriting-based person recognition system and to support user interaction, a GUI was developed with Python. The GUI supports the users in uploading a handwriting image from outside the system and choosing the classifying algorithm to be used, as shown in Fig. 5. Once the "Classify" button is clicked, the system validates the image with the pre-trained CNN feature extractor and the chosen classifier before displaying the identified name of the author on the screen. The interface provides a real-world demonstration of model performance and displays its usage in amicable software.

Table 2. show the summary of results for all algorithm used.

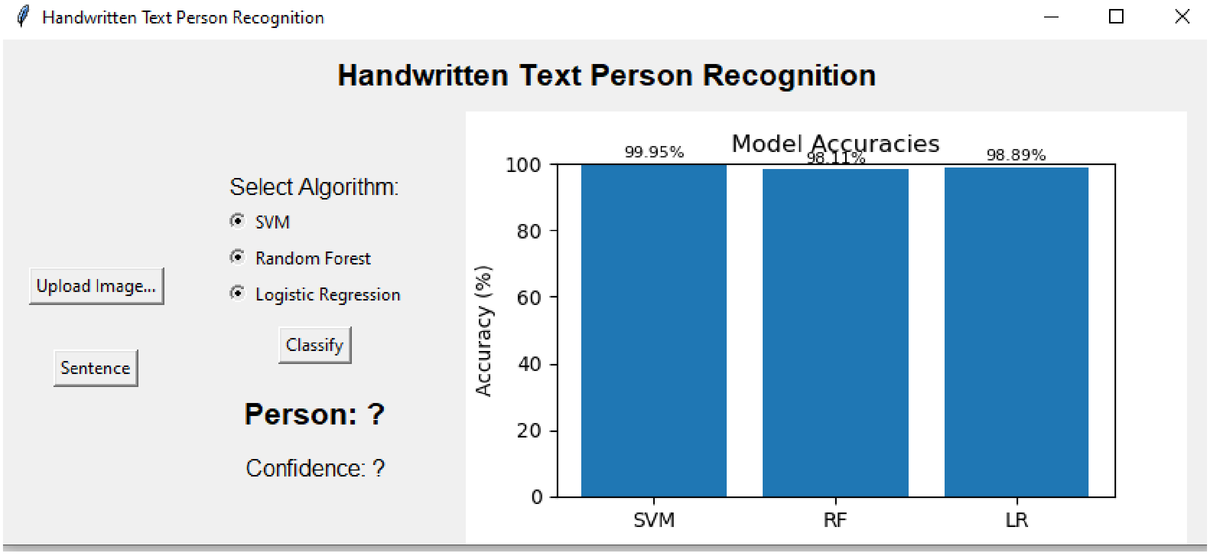

Fig. 8. GUI Window.

5. Discussion

The results of the work suggest the effectiveness of this proposed framework for handwriting-based people identification. The feature extractor in the role of CNN obtained a testing accuracy of 99.92%, while integrating deep features with a classical classifier obtained excellent results, primarily SVM, which obtained 99.95%. The cause behind these perfect results is data that was collected employing Graphic Tab; hence, in this manner, it doesn't include noise or varying illumination, and all the data is good to use.

When comparing the results with those of Fiel et al. , the superiority of the proposed system in this work is clearly evident. The test accuracy using CNN+SVM reached 99.95%, while Fiel and colleagues' results ranged from 94.6% on the IAM set to 97.2% on the CVL set[15]. This difference is primarily attributed to the nature of the data used; while Fiel relied on non-congruent data, where texts differ between training and testing, a more complex scenario that impacts generalizability, this work relied on more homogeneous data with a smaller number of authors, which helped achieve nearperfect results. However, the methodological convergence in both studies—using CNNs to extract features with an SVM classifier—confirms the effectiveness of this framework, noting that future challenges lie in testing the model on larger, more diverse datasets to ensure its generalizability in real-world biometric applications.

6. Conclusion and Feature Work

This work presents a successful application of a handwriting-person identification system involving both CNN feature extraction and traditional classifiers. The overall system performed almost perfectly, and CNN+SVM attained a maximum level of 99.95%, reflecting the power of deep features in expressing unique writing patterns. Its own application relevance is evident in enabling a powerful and easy-to-operate GUI system capable of supporting applications in biometric verification and security.

But this current arrangement relies on uniformly acquired data within constrained settings and is perhaps limited in level of generalizability. We need to test the model in the future on larger and differing sets, like non-congruent handwriting samples and noisy samples within natural scenes, on multiple language in order further to validate its extensibility and usability within realistic systems.

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