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Arabic writer identification for children using optimized adversarial-attention and dynamic hybrid classification

Identificación de escritores árabes para niños utilizando atención adversarial optimizada y clasificación híbrida dinámica

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ABSTRACT

Arabic handwriting recognition is an essential domain in computer vision research. However, its complexity, the intricate nature, varied writing techniques, and overlapping vocabulary of texts have resulted in a scarcity of published studies in this field. This paper proposes a model that addresses Arabic writer identification for children, in which an Adversarial Attention Variational Autoencoder is used for feature extraction and the Binary Pelican Optimization Algorithm is utilized for feature reduction. Additionally, the paper suggests a new classification model through a Dynamically Routed Hybrid Classifier (ResNet + DenseNet). To analyze the performance of the proposed model, the QUWI and Khat datasets were used. The results demonstrate that, for both datasets, a high accuracy of 98.8% is achieved, the highest result among all relevant work described in the paper. This suggests that the system achieves high accuracy and offers a novel way to improve writer identification through the use of optimization algorithms and advanced machine learning techniques.

Keywords: machine learning; variational autoencoders; BPOA; DenseNet; ResNet

RESUMEN

El reconocimiento de escritura árabe es un dominio esencial en la investigación de visión por computadora. Sin embargo, su complejidad, la naturaleza intrincada, las variadas técnicas de escritura y el vocabulario superpuesto de los textos han resultado en una escasez de estudios publicados en este ámbito. Este artículo propone un modelo que aborda la identificación de escritores árabes para niños, en el cual se utiliza un modelo de Autoencoder Variacional con Atención Adversarial para la extracción de características y el Algoritmo de Optimización de Pelícano Binario para la reducción de características. Además, el artículo sugiere un nuevo modelo de clasificación mediante un Clasificador Híbrido de Enrutamiento Dinámico (ResNet + DenseNet). Para analizar el rendimiento del modelo propuesto, se utilizaron los conjuntos de datos QUWI y Khat. Los resultados demuestran que, para ambos conjuntos de datos, se alcanza una alta precisión del 98,8%, el resultado más alto entre todos los trabajos relevantes que describimos en el artículo. Esto sugiere que el sistema logra una alta precisión y ofrece una forma novedosa de mejorar la identificación de escritores mediante el uso de algoritmos de optimización y técnicas avanzadas de aprendizaje automático.

Palabras clave: aprendizaje automático; autoencoders variacionales; BPOA; DenseNet; ResNet

1. INTRODUCTION

In the digital age, handwritten text picture writer identification remains a significant research topic with applications spanning from digital security to forensic analysis and historical document attribution (Diaz et al., 2019). Since handwriting is still a unique biometric identifier, developing trustworthy and accurate writer identification methods is essential (Pawan et al., 2024).

It is challenging to identify a writer due to the complex relationships between different writing styles, which are influenced by a wide range of factors like physiology, education, and personal habits (Altwaijry et al., 2020). Besides adult handwriting. As kids utilize technology more and more for both educational and entertaining purposes—such as smartphones and tablets—recognizing their handwriting is becoming a crucial component of many applications. Writing by hand with a finger or a stylus is increasingly the favored method of user input (Ullah et al., 2022).

There are currently more than half a billion Arabic speakers worldwide, making it one of the most widely spoken languages worldwide and one of the most widely used foreign languages in the Middle East and North Africa. The 28 letters that make up the Arabic language in conventional writing are taken from the script of the holy Quran and are typically written from right to leftCertain letters can have a varied appearance depending on whether they are at the beginning, middle, or end of the word; in other words, a letter's shape can change depending on where it is in the word. A common issue that faces all handwriting recognition language systems is the variation in font and letter size between handwriting from different people (Alrobah et al., 2021).

Automatic recognition of Arabic characters is still difficult since several research have found that different variations might be seen in the handwriting of the same person during data collecting. Similarly, Diminished Linguistic Variety: Arabic children's literature frequently employs simplified language and a small vocabulary, much like that of other languages (Mustafa et al., 2020). When linguistic complexity is reduced, style cues become less noticeable, which might make it challenging to distinguish between writers. Repetitive patterns: The use of wellknown phrases and repetitious sentence patterns to make the text kid-friendly might lead to similarities between the works of many authors. Arabic handwriting recognition is particularly difficult because of the following: The characteristics of Arabic script (e.g., cursive form, changeable letter size, varying letter shape depending on its position...), the vast variation in handwritten human handwriting, the lack of big and publicly available datasets, and the variety of handwritten styles (Younis et al., 2022). Handwriting recognition problem has been studied using many methods, such as: support vector machines (SVMs), K-nearest neighbors (KNNs), neural networks (NNs), and, recently, convolutional neural networks (CNNs) (Bennour et al., 2024).

Traditional methods have often relied on manually crafted features, which may fail to capture the subtle nuances that distinguish one writer from another (Trivedi et al., 2021). To address these limitations, Traditional methods struggle to capture subtle, unique characteristics of handwriting. There's a need for adaptive, comprehensive feature extraction techniques that can handle diverse writing styles and conditions while maintaining consistency across samples from the same writer and High-Dimensional Feature Spaces and Existing classification algorithms often fail to effectively model the complex, hierarchical, and spatial relationships in handwriting styles. This results in suboptimal performance, particularly when distinguishing between writers with similar styles and the dynamic nature of handwriting, influenced by various factors like writing speed and emotional state, requires robust systems capable of handling these variations while maintaining high accuracy. We lead to proposes a novel framework that combines feature extraction using Adversarial Attention Variational

Autoencoders (AAVAEs) (Trojovský et al., 2022), feature reduction through a binary Pelican Optimization Algorithm (POA), and classification via a dynamically routed hybrid model integrating Res Networks and Denc Net (Zhang et al., 2022).

The use of AAVAEs for feature extraction represents a significant advancement over conventional techniques. By incorporating adversarial training and attention mechanisms into the variational autoencoder architecture, we can generate more discriminative and robust features that capture the essence of a writer's style. However, the high-dimensional feature space produced by AAVAEs can lead to computational inefficiencies and potential overfitting. To mitigate these issues, we introduce a binary Pelican Optimization Algorithm for feature reduction. This nature-inspired metaheuristic, inspired by the foraging behaviour of pelicans, offers an efficient means of selecting the most relevant features while maintaining the integrity of the writer's signature style. The classification stage of our framework employs a dynamically routed hybrid classifier that combines the strengths of ResNetworks and Dence Net. ResNetworks, the dynamic routing mechanism allows for adaptive learning of the most salient features for each writer, potentially leading to improved accuracy and robustness.

2. RELATED WORKS

As showed in the Tabel 1. The Morera et. al. introduced Convolutional neural networks are the foundation of them approach because they have demonstrated superior ability to extract highquality features in comparison to manually constructed ones and attain 70% precision on the Khat dataset (Morera et al., 2018). The authors in (Rehman et al., 2019) they use handwritten text line images in the languages of Arabic and English to identify a writer using a deep transfer convolutional neural network (CNN). through QUWI DataSet. They assess how several CNN freeze layers—Conv3, Conv4, Conv5, Fc6, Fc7, and fusion of Fc6 and Fc7—affect the writer's identification rate. The AlexNet architecture is used to separate distinct visual features from several picture patch representations produced by improved preprocessing methods. A support vector machine classifier is then given the characteristics that were retrieved from the patches. By utilizing the frozen Conv5 layer, we were able to achieve the highest accuracy of 92.78% on English, 92.20% on Arabic, and 88.11% on the mixture of Arabic and English. Maaz et.al. proposed Convolutional Neural Network (CNN) construction This is helpful for obtaining information about features and subsequently categorizing the data; so, features are not required to predefine This study's tests were carried out on photos of Arabic handwritten manuscripts from the ICFHR2012 dataset, which included 202 writers and three texts per writer. The suggested approach produced a 98.2426% classification accuracy (Maaz et al., 2020) the authore in (Mustafa et al., 2020).

They use a deep learning approach called Multi-Dimensional Long Short-Term Memory (MDLSTM) networks and Connection-ist Temporal Classification (CTC). The MDLSTM has the benefit of scanning Arabic text lines in all directions (horizontal and vertical) to detect dots, diacritics, strokes, and tiny inflammation. The data-augmentation with a deep learning strategy achieves a better and more promising improvement in results on the KHATT dataset, with 80.02% Character Recognition (CR) compared to 75.08% as the baseline. The authres in (Rabaev et al., 2022) They suggest a unique way to design a B-CNN using ResNet blocks. B-ResNet fared better than other models in gender categorization on the KHATT and QUWI datasets, scoring 88.33 for QUWI and 76.17 for Khat Dataset. Mechanical et.al. suggest the Hybrid Deep Learning Method and Bee Colony Optimization Algorithm The proposed network employs the bee colony method in the middle layers of a deep convolutional neural network for the first time, with the goal of optimizing the parameters and enhancing learning performance, as well as improving the accuracy of author identification.and obtain 98.5% regarding the QUWI data set (Libo et al., 2024).

The authors in (Ullah et al., 2024) introduce Using DCNN for feature extraction, Bidirectional Long-Short Term Memory (BLSTM) for sequence recognition, and Connectionist Temporal Classification (CTC) loss function on the KHATT database, they present a deep learning model that is trained from scratch. An image-based sequence recognition framework that only requires line-level segmentation is established by the training phase, which produces impressive results: an 84% identification rate at the character level and a 71% recognition rate at the word level on the test dataset.

Table 1.
Summarize Writer identification

Reference	Year	Dataset	Model	Accuracy
Morera et al.	2018	Khat	CNN	70%
Rehman et al.	2019	QWUI	CNN+SVM	88%
Maaz et al.	2020	ICFHR2012	CNN	98.2%
Ahmad et al.	2020	Khat	MLSTM+CTC	75.02%
Rabaev et al.	2022	Khat+QUWI	CNN +ResNet	88.% for QUWI 76% for Khat
Mechanical et al.	2024	QUWI	CNN + Bee Colony Optimization Algorithm	98.5%
Aabed et al.	2024	KHat	DCNN + MLSTM and CTC	71%

3. DATASET

For the experiments, we used KHATT and QUWI datasets, which are publicly available.

KHATT (KFUPM Handwritten Arabic Text) dataset] was presented at the 13th International Conference on Frontiers in Handwriting Recognition (ICFHR) in 2012, with the goal of facilitating character recognition research for Arabic script. Every writing style is represented in this dataset. This 4000-paragraph data was created by 1000 authors from various countries, age groups, genders, and educational levels.

The dataset known as QUWI, or Qatar University Writer Identification: Arabic and English handwritten documents are included. The handwriting of 1017 authors is included in the entire dataset; each author contributed four pages, two in Arabic and two in English. Several competitions used subsets from the QUWI dataset, such as ICFHR 2016, ICDAR 2013, and ICDAR 2015. We employed the QUWI ICDAR2013 subset for this investigation.

4. PROPOSED MODELS

In the domains of automated document processing systems, historical manuscript verification, and forensic investigation, writer identification is a crucial task. standard techniques frequently rely on manually created features and standard machine learning algorithms, which might not adequately capture the subtle differences between each handwriting style. In order to get over these restrictions, this thesis presents a revolutionary approach to writer identification using cuttingedge deeplearning algorithms. Adversarial Attention Variational Autoencoders (AAVAE) are included into our methods for feature extraction, guaranteeing that the features extracted are indicative of the distinct writing styles and discriminative.

The adversarial component strengthens the robustness of the features by training the model to generate realistic and readable handwriting representations. To refine the feature set even further, we use the binary Pelican Optimization Algorithm (BPOA) for feature reduction. This optimization technique increases the model's efficiency and reduces computational complexity without compromising accuracy by effectively selecting the most crucial features.

We present a dynamically routed hybrid classifier that combines Dense Net and Res-Networks (ResNet), after feature extraction and reduction. This hybrid model uses Dense Net's lightweight yet robust architecture for image classification tasks, while ResNet's benefits in capturing spatial hierarchies and variations within handwritten text are leveraged. Our results demonstrate the potential of hybrid neural networks, optimization methods, and adversarial learning combined for difficult pattern recognition tasks like writer identification.

This work provides a strong framework that can be applied to other similar problems in text and picture analysis, in addition to furthering automated handwriting analysis. The proposed methodology offers a feasible path for additional investigation and practical implementations in several domains, such as forensic and historical document interpretation. The detailed flow chart of the recommended methodology is provided in Fig. 1.

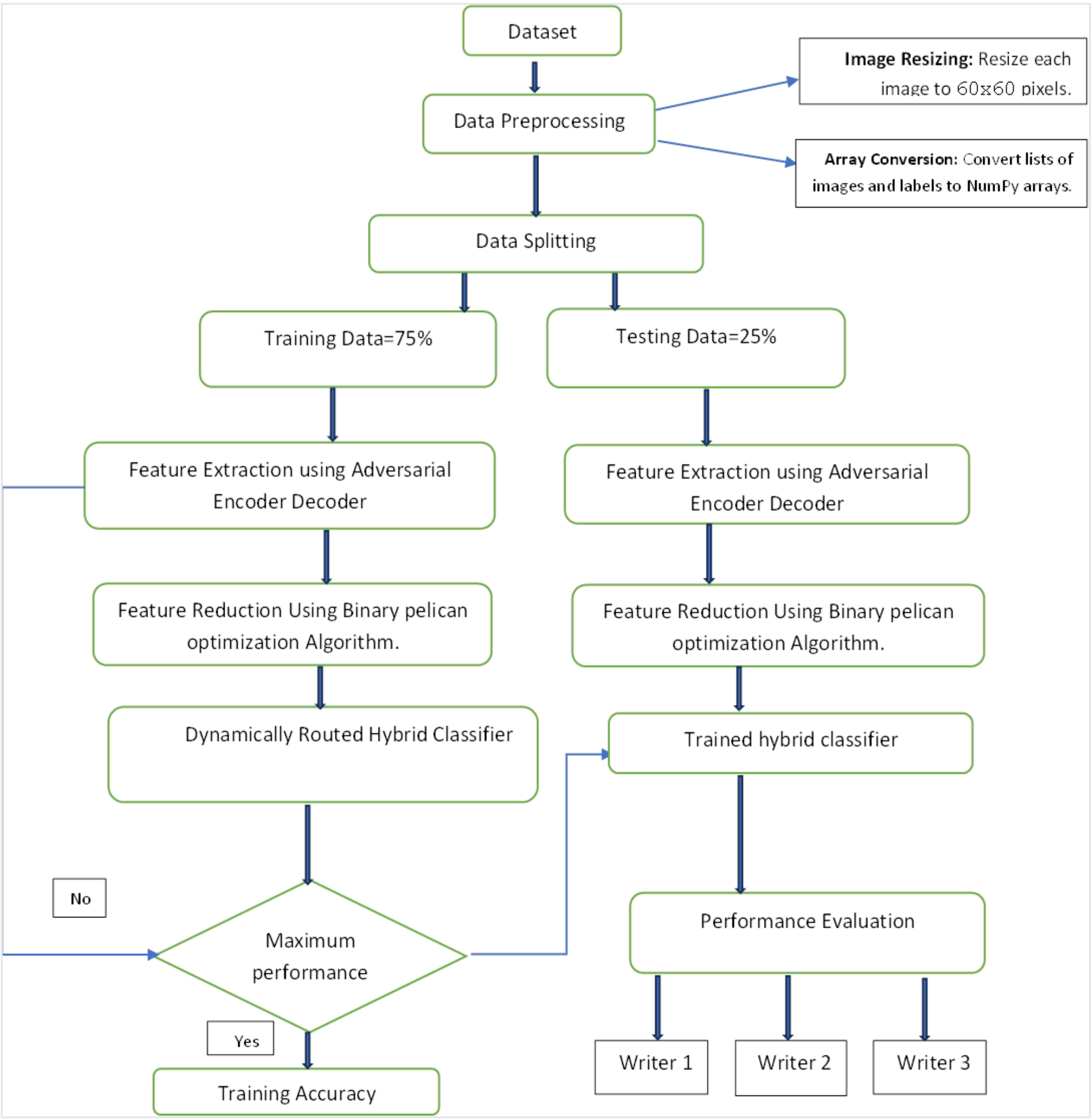

Figure 1. *Proposed Classification Framework*

The Fig.1 introduce the proposed system in General and now we explain the all parts of the proposed system in details.

5. FEATURE EXTRACTION USING ADVERSARIAL ATTENTION VARIATIONAL AUTOENCODERS

In this phase, we employ Adversarial Attention Variational Autoencoders (AAVAE) to extract robust and discriminative features from handwritten text images. The AAVAE architecture combines the strengths of Variational Autoencoders (VAEs) and adversarial learning. VAEs provide a probabilistic framework that enables the learning of latent representations by mapping input data to a latent space. The attention mechanism ensures that the model focuses on the most relevant parts of the handwriting, enhancing the quality of the features extracted. Adversarial learning involves training a discriminator alongside the encoder-decoder network of the VAE, compelling the encoder to generate features that are indistinguishable from the true data distribution. This adversarial setup promotes the generation of highquality and representative features, which are crucial for accurate writer identification. The feature extraction and classification flow are shown in Fig. 2.

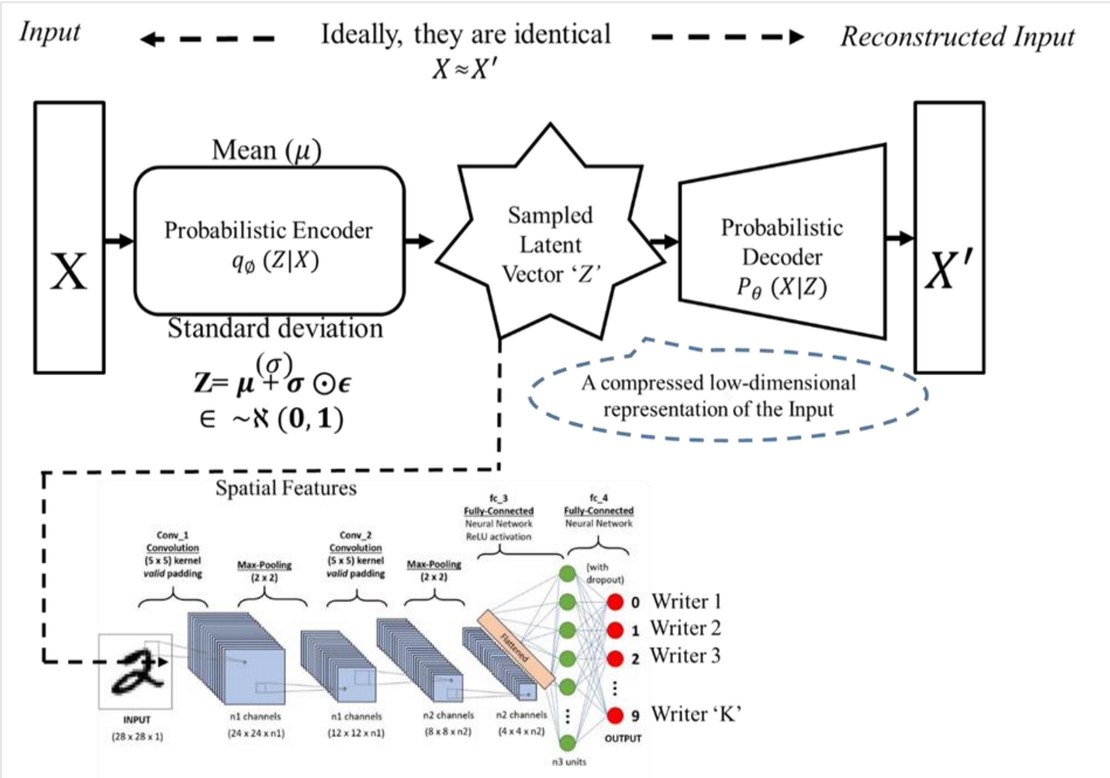

Figure 2. *Feature Extraction and Classification*

GANs are used to generate synthetic handwriting samples that resemble real handwriting. This augmentation increases the size and diversity of the training dataset, improving the robustness and generalization of the model. By training on a more varied dataset, the model can better handle different handwriting styles and variations, leading to more accurate gender classification. In trying to generate data that is identical to genuine samples, the generator synthesizes data samples from random noise. The discriminator checks whether the samples are legitimate and makes a distinction between produced and actual data. It builds up with a fully connected layer network architecture. The generator and discriminator are trained simultaneously in a zerosum game. The generator tries to produce convincing fake data to fool the discriminator, while the discriminator improves its ability to detect fake data. This iterative process continues until the generator produces highquality synthetic samples that true data is becoming harder for the discriminator to discern. The suggested adversarial generative network is shown in Fig. 3.

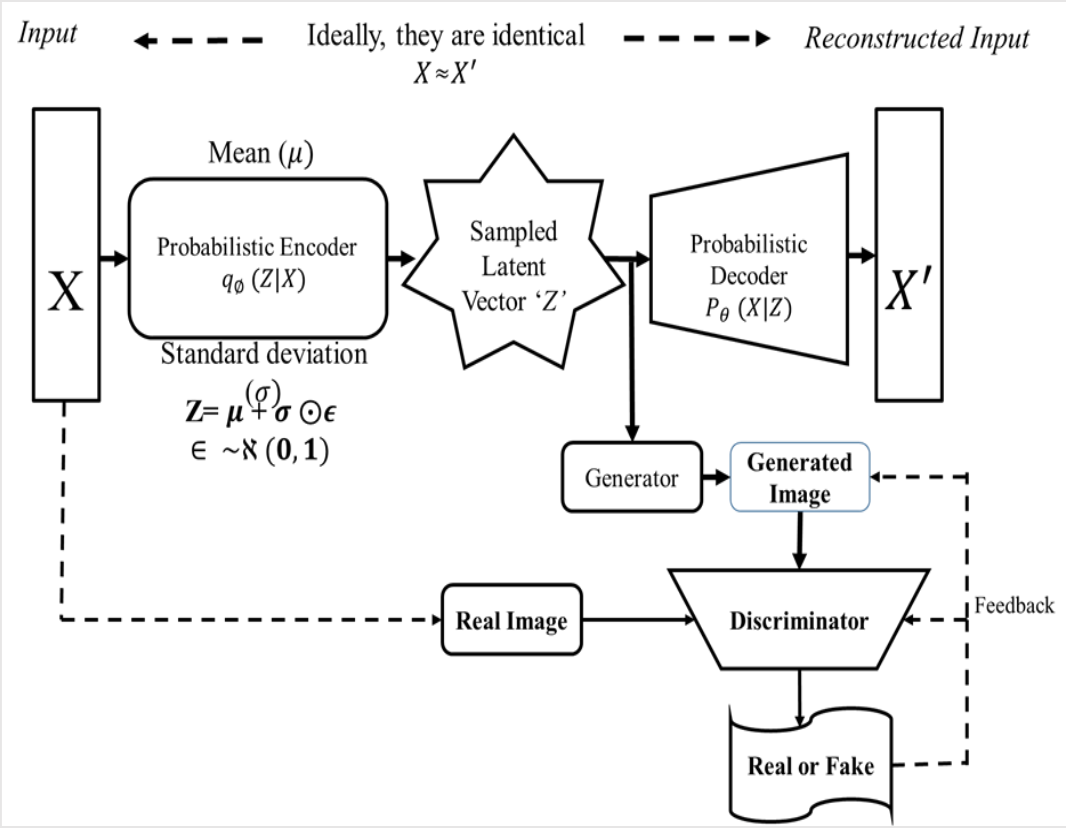

Figure 3. *Proposed Generative Adversarial Network for Data Generation*

6. FEATURE REDUCTION USING BINARY PELICAN OPTIMIZATION ALGORITHM (BPOA)

Following feature extraction, we employ the Binary Pelican Optimization Algorithm (BPOA) for feature reduction. The BPOA algorithm is a natureinspired metaheuristic that draws inspiration from pelican foraging behavior. In order to identify the most informative features, this algorithm is skilled at sifting through and taking advantage of the search space. To limit the curse of dimensionality, lower computational overhead, and improve the model's generalization capabilities in the context of writer identification, feature reduction is crucial. Subsets of features are iteratively evaluated by BPOA, which keeps track of whether features are redundant or irrelevant and chooses the ones that contribute most to the classification objective.

This phase ensures that the final feature set is compact yet highly informative, leading to more efficient and effective writer identification.

We use the fitness function for BPOA to balance between minimizing the number of selected features and minimizing the classification error. As shown in equation

Fitness Functon

$$\text{Fitness} = \alpha 1 \times \left(\frac{\text{Number of Selected Features}}{\text{Total Features}}\right) + \alpha 2 \times \text{Classification Error} \ldots\ldots (1)$$

This fitness function is used to guide the optimization process, where lower fitness values indicate better solutions (i.e., fewer selected features and lower classification error).

By applying this method, one can develop a more effective writer identification system that is not only accurate but also computationally efficient by focusing on the most relevant features.

7. CLASSIFICATION USING DYNAMICALLY ROUTED HYBRID CLASSIFIER (RES NET + DENSE NET)

The third phase involves the classification of handwriting features using a dynamically routed hybrid classifier that combines Res Networks (Res Net) and Dense Net. First, we use Res Net only for classification and Dense Net once for classification, but the accuracy was in the range (86-89) for the two data sets and then dynamically routed hybrid classifier that combines Res Networks (Res Net) and Dense Net. That achieve high accuracy. Res Networks are designed to capture spatial hierarchies and relationships between features, making them particularly suitable for recognizing complex patterns in handwritten text. Res Nets use dynamic routing algorithms to ensure that information flows between layers in a manner that reflects the spatial arrangement of features. Dense Net, on the other hand, is a lightweight convolutional neural network that balances computational efficiency and performance. We may take advantage of the advantages of both architectures by combining Res Net and Dense Net: Dense Net's efficiency and Res Net's capacity to retain spatial information.

The writer identification process is more reliable and accurate with the help of this hybrid model. Here, we used the attention mechanism to enhance the proposed classifier's discrimination performance. By enabling the model to concentrate on the most crucial elements of the handwriting samples, attention mechanisms enhance the effectiveness and precision of feature extraction. During several processing stages, attention can dynamically modify which portions of the incoming data to focus on, making sure that the most pertinent characteristics are highlighted. In order to determine each component of the incoming data's relevance to the current job, the mechanism calculates attention scores for each component. The attention scores are used to weight the input data, assigning greater weight to the sections with higher scores.

This helps the model focus on crucial handwriting features, such as stroke patterns and character shapes, which are indicative of gender. Autoencoders for effective dimensionality reduction and feature learning, and attention mechanisms for focused feature extraction—the proposed gender classification framework achieves a richer and more precise feature extraction process. This leads to improved overall performance, higher accuracy, and better generalization in distinguishing between child and adult handwriting. And the figure4 proposed the model Architecture.

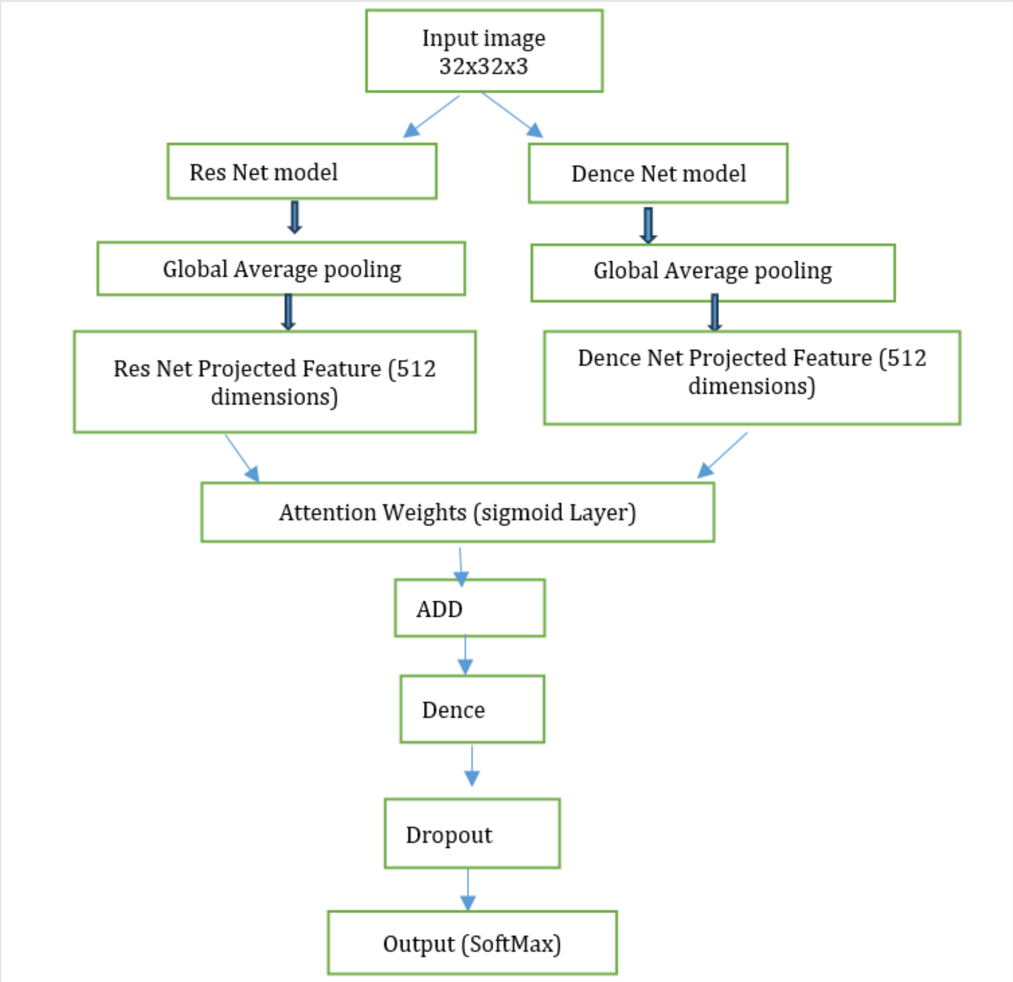

Figure 4. *Illustrate the Model Architecture*

In fig. 4 the Input Layer: The input to the model is a 32x32x3 image. ResNet Component: ResNet50 is used to extract features from the input image. The output features are globally averaged to reduce dimensionality. DenseNet Component: Dense-Net121 is similarly used to extract features from the input image, with a global average pooling applied to the output. Projection Layers: Both the ResNet and DenseNet features are projected to a common dimensionality (projection dim = 512). Attention Mechanism: The model applies attention weights to both ResNet and Dense Net features. These weights determine how much importance to give to each set of features when combining them. Feature Combination: The weighted features from Res-Net and DenseNet are combined (summed together).Fully Connected Layers: The combined features are passed through dense layers for final classification. Output Layer: The final output layer uses a softmax activation to classify the input into one of the target classes (e.g., different writers).

8. EXPERIMENTAL RESULTS

The proposed hybrid model is very robust because it can be applied with children writer and Adult writers and we achieved high accuracy rate in the both. To evaluate the efficiency of the proposed models, we use several evaluation metrics, including Recall, F1_score, Accuracy, and Precision. For QUWI dataset, we apply the Dense net only and Resnet 50 only and we achieve accuracy 88 and 86 then we use Dynamically Routed Classifier (Resnet + Dence net) and we achieve high accuracy 98.8 As shown in Chart 2.

Table 2.

Summarize the result of classification rate on QUWI Dataset

Model	Accuracy	Precision	Recall	F1_score
DenseNet	88	79	85	81
Resnet50	86	78	85	80
Proposed	99	97	98	97

For the Khat Dataset, we apply the Dense net only and Resnet 50 only and we achieve accuracy 89 and 87 then we use Dynamically Routed Classifier (Resnet + Dence net) and we achieve high accuracy 98.8 As shown in Chart 3.

Table 3.

Summarize the result of classification rate on KHATT Dataset

Model	Accuracy	Precision	Recall	F1_score
Densenet	89	78	84	82
Resnet50	87	79	83	80
Proposed	99	98	96	97

The fig. 5 illustrate Both accuracies) on training and validation data (exhibit oscillation at first, but after around 60 epochs, they stabilize, get better, and finally align rather nearly near 1.0, suggesting strong model performance and generalization.

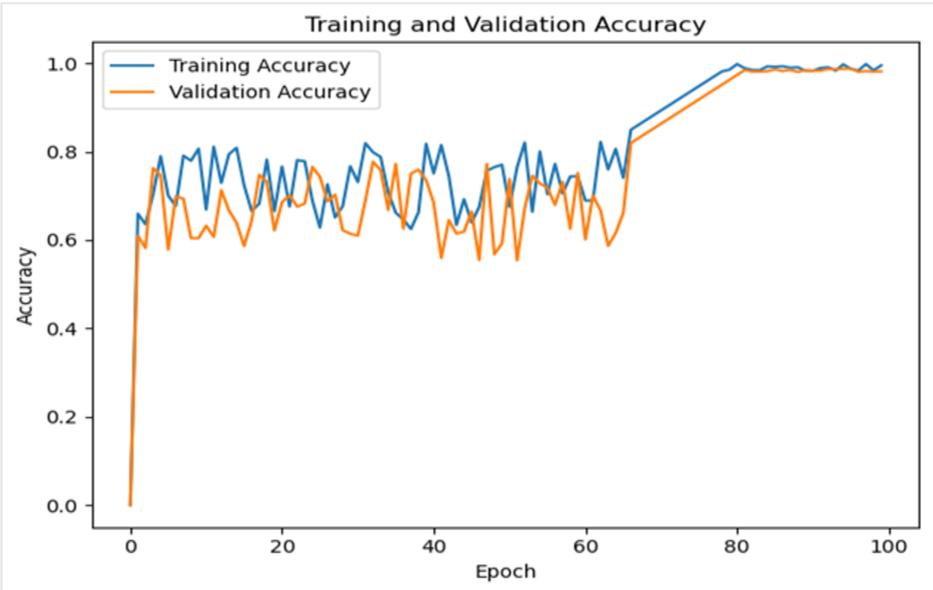

Figure 5. *Illustrate Training and Validation accuracy*

A multiclass classification model's Receiver Operating Characteristic (ROC) curve is depicted in the fig. 6. Plotting the True Positive Rate (sensitivity) versus the False Positive Rate for different threshold values results in lines that indicate distinct classes.

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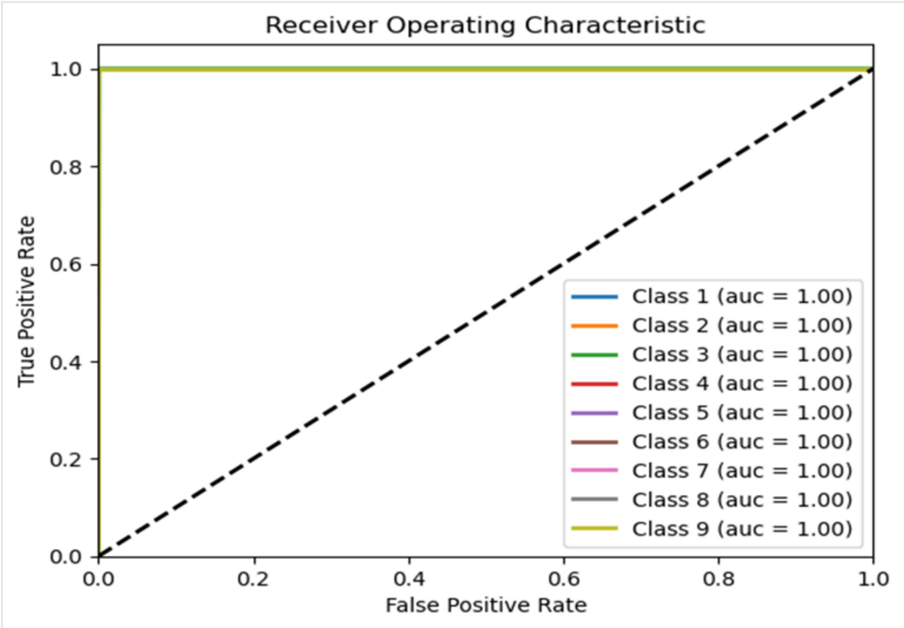

Figure 6. *Illustrate ROC Curves.*

The fig. 7 depicts a confusion matrix for a multiclass classification model. The matrix compares the actual labels (Y-axis) to the expected labels (X-axis). Overall, the confusion matrix demonstrates that the model is highly accurate with little errors.

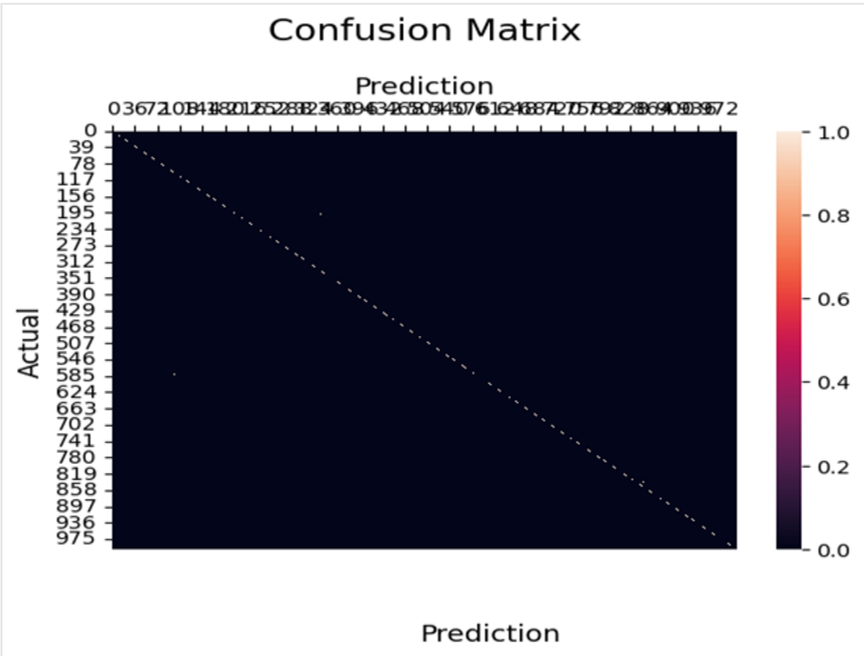

Figure 7. *Illustrate Confusion Matrix*

9. CONCLUSION AND FUTURE WORK

Each phase of our approach contributes to the overall effectiveness of the writer identification system. The integration of AAVAE for feature extraction that Enhanced ability to capture both global and local handwriting characteristics and to handling the complexity and variability in handwriting styles, BPOA for feature reduction Efficient method for selecting the most relevant features from high-dimensional AAVAE outputs and Potential for improving computational efficiency and model generalization, hybrid classifier combining ResNet and Dense Net for classification. This multiphase approach addresses the complexities of handwriting analysis, offering significant improvements in accuracy and efficiency over traditional methods. The advantage of this Hybrid High Accuracy: Combining ResNet and DenseNet ensures that the model captures a wide range of features, leading to more accurate writer identification. Flexibility: The attention mechanism allows the model to adapt to different inputs, focusing on the most relevant features for each specific case.

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CONFLICT OF INTEREST

There is no conflict of interest related to the subject matter of the work.

AUTHORSHIP CONTRIBUTION

Conceptualization, data curation, formal analysis, fund acquisition, research, project management, software, monitoring, validation, visualization, writing - original draft, writing - proofreading and editing: Najem & Muhanad.

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