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DeepNeutroBiLSTM: A Hybrid Neutrosophic and CNN-BiLSTM Framework with Sobel-Based Indeterminacy for Arabic Handwritten Character Recognition

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Abstract.
The numerous valid forms of Arabic handwritten characters, the structural similarities between these characters, and the noise caused by scanning results in handwriting recognition being very difficult. This study's contribution is a novel deep learning framework called DeepNeutroBiLSTM, which combines neutrosophic uncertainity modeling, Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) to create a superior handwwiting recogniton accuracy and robustness to handwriting variability and image noise.
These methods form five main steps of the process. They are: Pre-Processing and Data Partitioning, Neutrosophic Representation, Feature Extraction, Classification, and Post-Processing. The second step is related to Neutrosophic Representation, when an image of the character is divided into three parts, namely Truth, Indeterminacy, and Falsehood. The latter is obtained through integration of Fixed Neutrosophic Transform and Learnable Neutrosophic Layer. One of the most important aspects of the proposed framework is the Indeterminacy Representation that uses the Sobel Operator.
The neutrosophic form will be processed using a CNN with hierarchical feature extraction, and then the dependencies within the features will be modeled using BiLSTM. Performance of both parts can be estimated by carrying out comparisons among several alternative systems: CNN, CNN-BiLSTM, CNN-Neutro, and CNN-Neutro-BiLSTM. The superiority of the suggested method was shown via evaluation of results gained when working with two different test corpora (AHCD and HIJJA). In particular, our system named DeepNeutroBiLSTM that used Sobel-based indeterminacy demonstrated accuracies of 98.39% and 92.92%, respectively, along with properly calibrated probability distributions on corpora AHCD and HIJJA.

Keywords: Arabic handwritten character recognition; Neutrosophic representation; Deep learning; Convolutional neural networks (CNN); Bidirectional long short-term memory (BiLSTM); Uncertainty modeling.

1. Introduction:

Due to the cursive nature of the Arabic script, the variability of writing styles and the use of diacritics, recognition of Arabic handwritten characters via automatic Optical Character Recognition (OCR) systems continues to be a challenge for those systems. Recent advancements using both Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have opened up new possibilities for increasing recognition performance. however, still hold some limitations, such as data scarcity and the complexity of many character shapes, therefore there is an ongoing need for further investigation in this area[1–3].
In recent years, advancements using deep learning patterns, including convolutional neural networks (CNNs), have been credited for remarkable progress made in the area of handwritten character recognition due to their ability to automatically identify the most important differences in raw image data[3, 4] . Additionally, sequential models such as Long Short Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) networks have contributed to greater improvements in the processing of handwritten information through their ability to predict what will come next based on previous patterns[1]. However, most of today's methods for handwritten character recognition and most neural network methods recognize or assume that each input pixel is equally reliable, resulting in a lack of recognition of the variances caused by things such as blur from ink diffusion on a page due to multiple characters stacked over one another, the degradation of characters as scanned images due to changes in the original image, or variances between different writers[1].
To cope with uncertainty in visual data, a new way to compensate for the limitations within fuzzy sets has been developed using neutrosophic sets[5]. Neutrosophics offer the ability to represent not only true values (T) or false (F), however they offer an additional component of indeterminate (I) for utilizing the uncertainty of data in processing tasks with high levels of variability or uncertainly. Neutrosophic sets have been developed over previous methods of classical/fuzzy set theory and were able to predict the uncertainty of image processing operations using neutrosophics instead of traditional methods. Neutrosophics have demonstrated a high level of precision in all areas of image processing. for example, noise reduction, Segmentation and Recognition of Patterns through their use in the handwriting recognition task due to the nature of the uncertainty in handwriting caused by noise, degradation and variability[6–8].
The frameworks of Neutrosopy applied to character-based handwriting recognition need modification by merging them with new neutrosophy techniques. still, the methods currently available using neutrosophy have limitations. The indeterminacy component, used for some of the neutrosophic methods in image and handwriting recognition, is created by an algorithm or heuristically as part of the image processing[9, 10] ,it does help improve robustness to these types of noise or degradation, but does not allow for the flexibility required to take full advantage of the representation learning ability seen in deep neural networks nor can it be jointly optimised to the recognition goal[11, 12] Thus, any existing neutrosophic deep learning models rely on assumptions regarding the uncertainty

contained in a dataset and are unable to learn from the data where these uncertainties would exist and therefore may have difficulty appropriately capturing all the possible variations that exist within a real dataset containing character-based handwriting. Therefore, the solution to these issues will require moving away from traditional manual neutrosophic model-based definitions of uncertainties and towards developing data-driven learnable uncertainty definitions.

In this work, a learnable framework for neutrosophic deep learning for the recognition of character instances in Arabic handwriting directly targets the identified gap. The major contribution of this work is a Learnable Neutrosophic Layer (LNL) that learns the indeterminacy component directly from the images using trainable convolutional filters. Unlike the conventional approach for neutrosophics, the Learnable Neutrosophic Layer allows the network to learn where the uncertainties appear as part of the learning process for the recognition task.

The incorporation of learnable neutrosophic representation within an architecture combining convolutional neural networks (CNNs) with bidirectional long short-term memory (BILSTM) networks has demonstrated improved effectiveness for Arabic handwriting recognition. This is due to the ability of each component in the architecture to learn both spatial and sequential dependencies[15, 16], in addition to increasing recognition accuracy through improved calibration and reliability of the resulting predicted probabilities[17, 18]. However, the improvement in the predicted probabilities as a result of the hybrid architecture has only recently been a focus of research in deep learning and has not previously been investigated thoroughly for Arabic handwritten character recognition[17, 18] .

To evaluate the effectiveness of each of these components within the framework, this study investigated various configurations of deep learning techniques. These configurations include basic convolutional neural networks, hybrid convolutional and BiLSTM architectures, neutrosophic-inspired convolutional neural networks with a fixed indeterminacy representation, and convolutional neural networks with a neutrosophic-inspired representation. By comparing these configurations, one can evaluate the effectiveness of uncertainty modeling and sequential learning in Arabic handwritten character recognition. Among these configurations, the DeepNeutro-BiLSTM architecture with a sobel neutrosophic representation yields the best results, thus validating the effectiveness of deep convolutional features, neutrosophic-inspired uncertainty, and sequential learning.

To evaluate the efficacy as well as the ability to generalize the new framework, rigorous experiments are carried out on two publicly available datasets for comparison: AHCD[19]and HIJJA[20]. A rigorous test framework is also adopted in evaluating the performance on a set of parameters including accuracy, macro-F1 score, ROC-AUC score, character accuracy rate, as well as expected calibration error. The experiments show that the new models outperform CNN, CNN-BiLSTM models as well as fixed neutrosophic models.

2. Related Work:

Considering its complexity and high practical value, Arabic Handwritten Character Recognition (AHCR) has been a widely studied subject in research. The traditional way of handling classification tasks, including k-nearest neighbors, support vector machines(SVM), and hidden Markov models, coupled with carefully designed feature extraction techniques like zoning, projection profiles, contour descriptors, and histogram representation and Freeman chain code based descriptors, has been employed in early research efforts [21, 22] , Fethi et al. proposed a progressive approach for Arabic character recognition based on a modified Freeman Chain Code that encodes character contours into compact directional representations. Their method improves the preservation of structural features of Arabic letters and enhances recognition performance compared with traditional chain code techniques[23, 24].

Farhaoui et al. proposed an Arabic handwritten character recognition approach based on Scale-Invariant Feature Transform(SIFT) features and a Bag-of-Visual-Words representation, where k-means clustering is used to construct a visual dictionary and an SVM classifier performs the final recognition of Arabic characters[25, 26]

However, their reliance on manual design made them more vulnerable to differences in handwriting variations and noisy data. Convolutional Neural Network (CNN), being the core base for feature extraction and classification, brought about a paradigm shift in Arabic Optical Character Recognition as well. The models, including LeNet, AlexNet, and different variations of VGG, achieved remarkable improvements on established benchmark datasets like AHCD and HIJJA [27]The first CNN model for handling Arabic handwriting came up in research by Al-Sawy et al., accomplishing better outcomes than traditional models[28], Convolutional neural networks (CNNs), which learn hierarchical visual features for classification, became the standard method with the development of deep learning[29, 30].

Building Upon these advances in technology, the combination between Convolutional Neural Network (CNN) with Bidirectional long short term memory network (BiLSTM) models allows both the spatial and sequential dependencies found in cursive Arabic writing to be captured simultaneously. Most recently, extensive research using Compositional Neural Networks (CNN) and Compositional Neural Networks/Long Short-Term Methhod Cursive Classification (CNN-LSTM) hybrid architectures have further established their usefulness while exposing limitations due to uncertainty and ambiguity related to character pattern recognition issues[25]. In addition, Bounour et al. [29] have shown that using attention-based mechanisms and the use of adaptive data augmentation techniques on the CNN/BiLSTM/CTC framework increases the growth of the model's ability to learn and recognize transition relationships in Arabic handwriting as well.

Though the capability to recognize both the spatial and temporal features was established in the CNN-BiLSTM models, the problem with the models remains the lack of an explicit solution for regions with ambiguous and degraded handwriting, which makes them less robust in dealing with ill-conditioned regions [31].To overcome this problem, the proposed solution in this research paper includes the design of DeepNeutroBiLSTM, which combines the CNN-BiLSTM model with a Learnable Neutrosophic layer that captures the truth, falsity, and indifference in every pixel.

Neutrosophic set theory, first introduced by Smarandache in [5],considers the information in three facets: truth, indeterminacy, and falsity. This method has been successfully utilized in image processing and most recently in character recognition of handwritten characters in an attempt to completely characterize the uncertainty in the images [32],[33]. Currently, all recent

neutrosophic-based methods have relied on manual-designed rules in the calculation of the indeterminacy membership in the form of entropy or gradients and thus lack the capability of optimizing deep learning networks.

Simultaneously, uncertainty modeling in deep learning has been addressed by some studies using Bayesian neural networks, ensemble learning strategies, and calibration procedures in [34], While these solutions are beneficial for measuring prediction confidence, they often lead to a complexity cost or uncertainty modeling considered solely from an evaluation perspective of model outputs. Therefore, direct uncertainty modeling based on this learning process has been less focused in the area of Arabic handwritten character recognition.

Despite these advancements, current CNNs and CNN-BiLSTM architectures generally assume that all input pixels have equal importance in the recognition process. In practice, handwritten characters often have uncertain regions due to ink diffusion, noise, writer variability, or poor scanning quality. These uncertain regions can have a detrimental impact on learned representations and robustness in character recognition. Neutrosophic theory is an appropriate mathematical theory for handling uncertain information in images; however, current approaches mostly employ manually designed indeterminacy functions, which limits their flexibility for different datasets and writing styles. As a result, there is an urgent need for developing deep learning-based character recognition models that can learn uncertainty representations from data while maintaining spatial and sequential dependencies in handwritten characters.

This study proposes a CNN-BiLSTM model with a neutrosophic learning component that estimates truth, falsity, and indeterminacy at the pixel level, which can be applied to complex problems like handwritten character recognition. By using indeterminacy as a model component that can be learned from the data, this approach allows for more flexible modeling of uncertain regions of an image within a deep learning framework. Moreover, different neutrosophic representations are also discussed, including entropy and gradient representations of indeterminacy, such as the sobel operator. Experimentation results show that the proposed DeepNeutroBiLSTM model with a neutrosophic representation using the sobel operator achieves the best results, thus validating the effectiveness of using uncertainty modeling within deep sequential learning for Arabic handwritten character recognition.

3. Methodology:

3.1 Problem Definition:

Let $D = \{(X_i, y_i)\}_{\{i=1\}}^{\{N\}}$ be a dataset of Arabic handwritten character images, where $X_i \in R^{H\times W\times 1}$ denotes a grayscale image and $y_i \in \{1, \dots, C\}$ represents its corresponding character class.

The objective of Arabic handwritten character recognition is to acquire a discriminative mapping.

$$f : R^{H\times W\times 1} \rightarrow R^{C} \qquad (1)$$

that correctly detects handwritten characters while staying resistant to noise, writing variability, and structural ambiguity in Arabic script.

Unlike traditional techniques, which depend on deterministic pixel representations, this study directly handles uncertainty at the representation level.

3.2 Overview of the Proposed Framework

Hence, the proposed model of DeepNeutroBiLSTM as a hybrid deep learning model utilizes a Learnable Neutrosophic Layer (L-Neutro), which is integrated with CNN-BiLSTM to allow for end-to-end learning through the integration of neutrosophic logic into the learning of features. This provides an additional avenue for defining uncertainty as compared to traditional deterministic models that do not explicitly address uncertainty within the learning of features. As depicted in **Figure 1**, the overall design of the system has four major components:

- **i** An L-neutro layer containing neural networks produces a neutrosophic representation of objects based on their learnable indeterminacy,
- **ii** A hierarchical spatial feature extraction method that is accomplished by utilizing convolutional neural networks.,
- **iii** The use of bidirectional long-short term memory (BiLSTM) networks to model the long-term dependence of sequential data,
- **iv** The implementation of fully-connected feed-forward neural networks followed by the use of a softmax decision function to classify object.

The complete framework of the proposed DeepNeutro-BiLSTM architecture can be characterized as a chain of three operations, which include neutrosophic representation learning, spatial feature extraction, and sequential modeling. The prediction function of the proposed architecture is formally defined by:

$\hat{y} = Softmax(BiLSTM(CNN(N(X))))$	**(2)**

Here, the notation N(X) represents the neutrosophic representation of the input image, CNN(•) represents hierarchical spatial feature extraction, and BiLSTM(•) represents contextual dependencies in the feature sequence. The expression highlights the fact that the proposed framework combines the learning of neutrosophic representations, spatial feature extraction, and sequential modeling in a unified framework of deep learning. Such integration enables the model to deal with the uncertainty of handwritten strokes explicitly, while at the same time incorporating spatial and contextual dependencies.

Algorithm 1: DeepNeutroBiLSTM Framework

Function: DeepNeutroBiLSTM(X)
Input:
$X \in \mathbb{R}^{H\times W\times 1}$: normalized grayscale handwritten character image
Output: $\hat{y} \in \{1, \dots, C\}$: $\hat{y} \in \{1, \dots, C\}$
Ensure: $\hat{y} \in \{1, \dots, C\}$
1: Normalize X to [0,1]
2: $T \leftarrow X$
3: $I \leftarrow \sigma(\phi(X;\ \theta))$
4: $F \leftarrow clip(1 - T - I, 0, 1)$
5:$N \leftarrow [T, I, F]$
6: $F_{spatial} \leftarrow CNN(N(X))$
7: $S \leftarrow Reshape(F_{spatial})$
8: H ← BiLSTM(S)
9: Classification
10: $\hat{y} \leftarrow softmax(W\ h + b)$
11: **return** $\hat{y}$

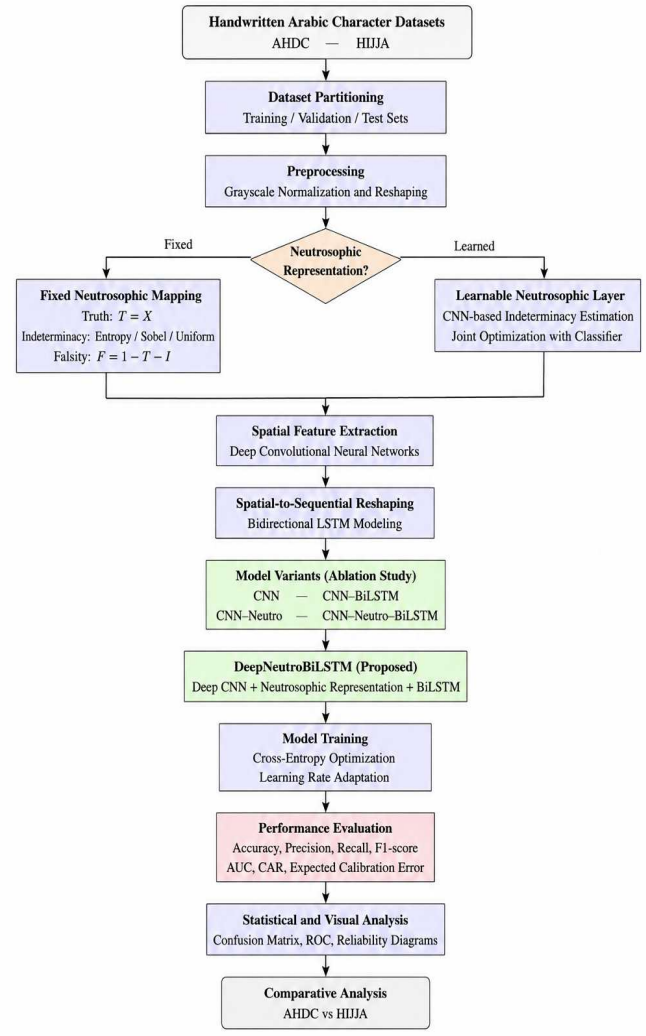


Fig 1. Architecture of the proposed **DeepNeutroBiLSTM framework**. The model integrates a learnable neutrosophic representation with a CNN–BiLSTM backbone to jointly model uncertainty, spatial features, and contextual dependencies for Arabic handwritten

This joint modeling of truth, indeterminacy, and falsity enables the framework to better capture uncertainty in handwritten characters and improves robustness to noise, writing variability, and structural ambiguity.

3.3 Learnable Neutrosophic Representation

In the neutrosophic domain, each pixel $\boldsymbol{x} \in \boldsymbol{\mathcal{I}}$ of a normalized grayscale image is represented by three complementary membership values:

$$N(x) = [T(x), I(x), F(x)] \quad (3)$$

Where:

- **Truth (T)**: The measure of confidence in the pixel belonging to the object.
- **Indeterminacy (I)**: The measure of uncertainty or ambiguity.
- **Falsity (F)**: Degree of non-membership.

Custom-defined neutrosophic methods have traditionally utilized predetermined operators for computing their indeterminacy component such as entropy or gradient magnitude. This can be beneficial, however, as these operators cannot be modified to fit all data sets or writing styles using this type of operation.

Among the operators based on the gradient, the Sobel operator is especially suited for the recognition of handwritten characters, as it enhances the stroke boundaries and local structural changes, which are very significant for distinguishing between visually similar Arabic characters.

The Learnable Neutrosophic Layer formally defines how to map an input image x to a neutrosophic triplet.:

$[T(x),\ I_{learned}(x), F(x)] = L - Neutro(x)$	(4)

For the purpose of systematically evaluating the effectiveness of uncertainty modeling and sequential feature learning, various architectural configurations are considered in the current research. These configurations include baseline convolutional neural network (CNN) models, CNN-BiLSTM models, neutrosophic CNN models based on entropy-based indeterminacy, models based on learnable indeterminacy representations, and the proposed DeepNeutroBiLSTM models. These models are trained in the same environment to determine the architecture that best enables Arabic handwritten character recognition.

3.4 Learnable Neutrosophic Layer

To address this restriction, we present the Learnable Neutrosophic Layer (LNL), which estimates the indeterminacy component directly from data.

Given an input image $\boldsymbol{X} \in \boldsymbol{R^{H\times W\times 1}}$, the neutrosophic representation is defined as:

$$T = X$$
$$I = \sigma(\phi(X;\ \theta))$$
$$F = clip(1 - T - I, 0, 1)$$

where:

- $\boldsymbol{\phi}(\cdot)$denotes a trainable convolutional mapping,
- $\boldsymbol{\theta}$ represents learnable parameters,
- $\boldsymbol{\sigma}(\cdot)$is a sigmoid activation ensuring $I \in [0,1]$.

More explicitly, the Learnable Neutrosophic Layer computes the neutrosophic components at the pixel level as:

$T(x) = X$	(5)

$I(x) = \sigma(W_I * x + b_I)$	(6)
$F(x) = 1 - T(x) - I(x)$	(7)

The symbol * indicates convolution, the function **σ(·)** represents the sigmoid activation, and both W_T and W_I represent learnable parameters. The result of this procedure is the neutrosophic tensor N(x), which is input into the CNN during the hierarchical feature extraction stage.
The output neutrosophic image is:

$N(X) = [T, I, F] \in \mathbb{R}^{H \times W \times 3}$	(8)

In addition to the learnable indeterminacy representation, this work also explores alternative neutrosophic mappings to assess the effectiveness of different uncertainty modeling strategies. For this purpose, the fixed indeterminacy operator using entropy and gradient magnitude is used. For the gradient magnitude operator, the Sobel operator is used to calculate the uncertainty regions due to edges in handwritten characters. The effectiveness of different indeterminacy representations is assessed using the same CNN-BiLSTM model.
For the gradient-based neutrosophic representation, the indeterminacy component can also be estimated using the Sobel operator, which captures local edge variations associated with stroke transitions in handwritten characters. The Sobel-based indeterminacy is defined as:

$I(x) = \frac{\mid \nabla_{sobel}(x) \mid - min}{max - min}$	(9)

where $\nabla_{sobel}(x)$denotes the gradient magnitude computed using the Sobel operator.
The Sobel-based indeterminacy representation has also been found to be particularly effective for the recognition of handwritten characters, where the boundaries of the strokes of the characters are critical for the differentiation of similar Arabic characters.
The result is then passed to the CNN back-end to enable multi-level feature extraction.
In the classical neutrosophic approach, the treatment of uncertainty is done in isolation from any evolving goal related to the character being recognized. This is in contrast to the Learnable Neuron Logic (LNL), where uncertainty and character recognition goals can be optimized simultaneously to enable the construction of an uncertainty representation sensitive to the specific problem at hand.

3.5 CNN–BiLSTM Backbone Architecture

3.5.1 Convolutional Feature Extraction

The CNN backbone comprises three convolutional blocks, each employing a kernel size of 3x3, with channel depth increasing from 64 to 128, and finally to 256. Following each block, batch normalization and ReLU activation functions are performed, which can ensure the reliable extraction of local stroke patterns as well as structural features.
In this CNN, the neutrosophic input can be mapped to a high-level spatial feature representation.

Formally, the spatial encoder computes:

$$F_{spatial} = CNN\big(N(X)\big)$$

3.5.2 Sequential Modeling with Bidirectional LSTM

The spatial arrangement of written Arabic characters is based on their relationships, and this relationship can be addressed by processing the characters sequentially. To address this relationship between each Arabic character and its neighbors, spatial feature maps are converted to sequences and then fed to a Bidirectional Long Short-Term Memory Network.
Given a sequence $\{f_t\}_{\{t=1\}}^{\{T\}}$, Formally, given CNN feature vectors f_t at time step t, the BiLSTM computes:

$$\vec{h}_t = LSTM(f_t, \overrightarrow{h_{t-1}}) \ , \overleftarrow{h_t} = LSTM(f_t, \overleftarrow{h_{t+1}})$$

and forms the bidirectional embedding:

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}]$$

This allows the model to include contextual information from both the forward and backward directions. This bidirectional modeling improves recognition between visually identical characters.
This hybrid model architecture allows the model to utilize both spatial stroke patterns and contextual dependencies, as well as robustness to variability in handwriting and noise in images.

3.5.3 Design Rationale of DeepNeutroBiLSTM

The architectural design of DeepNeutroBiLSTM is based on the complementarity of the strengths of neutrosophic representation learning, convolutional feature extraction, and sequential modeling.
To start with, neutrosophic representation specifically considers uncertainty in handwritten characters by splitting the input image into truth, indeterminate, and false components. With this, the model can focus more on ambiguous regions due to variability in writing, as well as overlapping strokes and noises. Second, the Convolutional Neural Networks (CNN) is employed to extract hierarchical spatial features from the neutrosophic representation. It has been observed that the CNN layers perform well in extracting the stroke patterns and structural characteristics of handwritten characters. Third, a Bidirectional Long Short-Term Memory (BiLSTM) network is used to capture contextual dependencies in the spatial feature sequence. The use of the bidirectional approach allows the architecture to use information from both the forward and backward directions, thus improving the discrimination between visually similar Arabic characters. Incorporating these three components into a unified deep learning architecture enables the proposed architecture to jointly handle uncertainty-aware representations, spatial stroke patterns, and contextual dependencies. This architecture significantly improves the robustness and discriminative ability of the proposed architecture in handling Arabic handwritten character recognition.

3.5.4 Classification and Learning Objective

The BiLSTM output is fed into fully connected layers, followed by a softmax classifier to get the final prediction.

$$\hat{y} = softmax(W\, h + b)$$

where $W$and $b$denote trainable parameters.
The model is trained using categorical cross-entropy loss:

$$L = -\sum_{c=1}^{c} y_c \, log(\hat{y_c})$$

and all parameters, including those of the learnable neutrosophic layer, are optimized jointly via backpropagation.

Algorithm 2: Training Procedure of DeepNeutro-BiLSTM

function: Train-DeepNeutroBiLSTM(D)
input $D = \{(x_i, y_i)\}_{\{i=1\}}^{\{N\}}$
1. **for** each epoch **do**
    1. **for** each batch **do**
    2. $\hat{\boldsymbol{y}} \leftarrow$ **DeepNeutroBiLSTM**$(\boldsymbol{X})$
    3. $\mathcal{L} \leftarrow$ **CategoricalCrossEntropy**$(\mathbf{y}, \hat{\mathbf{y}})$
    4. **Update all model parameters using backpropagation**
    5. **end-for**
2. **end-for**

3.5.5 Computational Complexity

The computational cost for the suggested layer of learnable neutrosophic features is not high, which limits the number of convolutions that can be performed on the image. The computational complexity for this layer increases linearly with the size of the input image. The computational complexity for this layer can be represented as follows:

$$\boldsymbol{O(H \times W \times k^2)}$$

Where Hand k are the dimensions of the image, and k is also the dimension of the kernel. Although many approaches to model uncertainty, which are based on a Bayesian inference or employ a technique called ensembles, generally require much more computationally expensive operations, this method provides a technique to model uncertainty with much lower computational costs.

3.5.6 Training Strategy

In order to test and assess the efficiency of the proposed model, the two widely accepted benchmarks for Arabic handwritten character recognition were used, namely AHCD, containing 28 characters, and HIJJA, containing 29 characters. For both benchmarks, the datasets were split into 80%, 10%, and 10% for training, validation, and testing, respectively, to ensure comparable class proportions for both datasets. Data augmentation was used to increase the capacity of the models to generalize and perform well across different handwriting styles for both datasets. The augmentation methods used include rotation of the characters based on their centers, translation, zooming (both magnification and reduction), and shearing (skew).

The model was trained end-to-end on the entire dataset for a total of 100 complete epochs. It was trained using Categorical Cross-Entropy as the Loss Function. It was optimized using the Adam Optimizer with an adaptive learning rate schedule to ensure that the model converges smoothly. It was regularized using Batch Normalization and Dropout (p = 0.3).

The model was evaluated for its performance through a variety of metrics, including Accuracy, F1-score, AUC, and CAR.

To evaluate the contribution of different components within the proposed framework, various architectural designs are considered, including CNN, CNN-BiLSTM, neutrosophic CNN, and hybrid models incorporating both neutrosophic and sequential learning approaches. This ablation study allows for a systematic evaluation of the specific role of uncertainty modeling and sequential feature learning towards overall recognition performance. This allows for the evaluation of the impact of uncertainty modeling and sequential feature learning on the performance of the recognition task.

4. Results and Discussion

4.1 Performance Summary

The table of contents of this document includes the performance evaluation of the experimental architectures against both the AHCD and HIJJA datasets; these tables can be found in tables 1 and 2. The performance of various architectural designs was determined based on their ability to implement neutrosophic uncertainty modelling and sequential feature extraction techniques, supporting the goal of improving Arabic handwriting recognition models through testing various experimental architectures (via the baseline CNN, the CNN-BiLSTM, neutrosophic CNN with entropy representation, neutrosophic CNN with learnable indeterminate representation and finally the creation of a new architecture called DeepNeutroBiLSTM).

4.2 Results on the AHCD Dataset

Table 1. Performance comparison of the evaluated models on the AHCD dataset.

Model	Test Acc.	F1	AUC	CAR
CNN	0.9643	0.9596	0.9990	0.9595
CNN–BiLSTM	0.9631	0.9608	0.9994	0.9607
CNN–Neutro (Entropy)	0.9542	0.9517	0.9989	0.9518
CNN–Neutro–BiLSTM (Entropy)	0.9762	0.9792	0.9997	0.9792
CNN–Neutro (Learned)	0.9571	0.9535	0.9990	0.9536
CNN–Neutro–BiLSTM (Learned)	0.9744	0.9751	0.9997	0.9750
DeepNeutro-BiLSTM (Sobel)	**0.9839**	**0.9821**	**0.9997**	**0.9822**

Table 2: Calibration and Computational Cost Comparison on the AHDC Dataset

Model	ECE ↓	Time (s) ↓
CNN	0.0254	150.00
CNN–BiLSTM	0.0293	305.66
CNN–Neutro (Entropy)	0.0159	**139.28**
CNN–Neutro–BiLSTM (Entropy)	0.0219	389.76
CNN–Neutro (Learned)	**0.0111**	161.92
CNN–Neutro–BiLSTM (Learned)	0.0214	428.48
DeepNeutro-BiLSTM (Sobel)	0.0119	1818.82

Tables 1 and 2 present the comparative performance of all evaluated architectures on the AHCD dataset of isolated handwritten Arabic characters.

The baseline Convolutional Neural Network (CNN) model achieves a test accuracy of 96.43% and an F1-score of **0.9596**, indicating a good deterministic baseline performance for the recognition task. Adding a Bidirectional Long Short-Term Memory (BiLSTM) layer to incorporate sequential dependencies into the model reduces the performance slightly to **96.31%**. This indicates that sequential dependencies do not play a major role in isolated character recognition tasks, where there are limited dependencies between characters.

However, the inclusion of sequential modeling with the addition of a Bidirectional Long Short-Term Memory (BiLSTM) layer does not produce a significant improvement with a decrease in accuracy from **96.43%** to **96.31%**. This indicates that sequential modeling does not produce a significant impact when processing isolated character images with minimal contextual dependencies.

The CNN - Neutro - BilSTM (Entropy) Model combines Entropy-based Neutrosophy with Sequential Models to provide significant performance improvements with test accuracy greater than **97.62%** and F1 scores greater than **0.9792**, demonstrating that combining models of Spatial Uncertainty with contextually learning features provides richer representations of generated features.

The proposed **DeepNeutroBiLSTM** architecture achieves the highest performance across all metrics:

- **Test Accuracy:** 98.39%
- **F1-score:** 0.9821
- **AUC:** 0.999741
- **CAR:** 0.9821
- **ECE:** 0.0119

Compared with the baseline CNN model, this corresponds to:

- **+1.96% improvement in test accuracy**
- **+2.25% improvement in F1-score**
- **≈50% reduction in calibration error**

The model proposed is superior due to a Sobel based uncertainty representation along with the use of the neutrosophic model of indeterminacy. The Sobel operator provides emphasis on the edge of strokes and the gradient change of each stroke as they change from one character structure to another and therefore is a key element in helping differentiate between characters that are visually similar (such as Arabic). The integration of the Sobel operator's gradient based indeterminate uncertainty representation allows for improved discriminative characteristics of the model when it comes to handwritten character recognition when utilizing the deep architecture.

Furthermore, the small gap between validation and test accuracy indicates **stable convergence and good generalization capability**.

4.3 Results on the HIJJA Dataset

Table 4. Performance comparison of the evaluated models on the HIJJA dataset.

Model	Test Acc.	F1	AUC	CAR
CNN	0.8796	0.8758	0.9962	0.8794
CNN–BiLSTM	0.8904	0.8852	0.9955	0.8893
CNN–Neutro (Entropy)	0.8879	0.8957	0.9972	0.8992
CNN–Neutro–BiLSTM (Entropy)	0.9058	0.9130	0.9975	0.9161
CNN–Neutro (Learned)	0.8923	0.8942	0.9969	0.8978
CNN–Neutro–BiLSTM (Learned)	0.8938	0.8978	0.9968	0.9018
DeepNeutro-BiLSTM (Sobel)	**0.9292**	**0.9322**	**0.9982**	**0.9349**

Table 5: Calibration and Computational Cost Comparison on the Hijja Dataset

Model	ECE ↓	Time (s) ↓
CNN	0.1029	391.99
CNN–BiLSTM	0.0972	824.29
CNN–Neutro (Entropy)	**0.0280**	**359.21**
CNN–Neutro–BiLSTM (Entropy)	0.0813	1022.11
CNN–Neutro (Learned)	0.0396	415.66
CNN–Neutro–BiLSTM (Learned)	0.0867	1126.90
DeepNeutro-BiLSTM (Sobel)	0.0456	5250.18

The HIJJA dataset is a more difficult recognition task because of the large variability of handwriting styles and the greater structural ambiguity of Arabic letters. Tables 4 and 5 show how well the results compare for performance, calibration quality and cost to compute for each of the different models on this dataset.

The baseline convolutional neural network (CNN) model achieves a test accuracy of **87.96%** and an F1-score equal to **0.8758**. This proves that the HIJJA dataset is more challenging compared to the AHCD dataset. By adding the concept of sequence using the CNN-BiLSTM model, we achieve a recognition accuracy of **89.04%** and an F1-score equal to **0.8852**. This proves that sequence modeling is more beneficial for datasets with more variability in handwriting.

When the entropy-based neutrosophic representation is combined with the sequential modeling, the CNN-Neutro-BiLSTM (Entropy) achieves a significant improvement in the recognition performance, with the test accuracy being **90.58%** and the F1-score being **0.9130**. This validates the fact that the combination of spatial uncertainty modeling with the sequential contextual learning results in more informative features for the handwriting patterns.

The proposed DeepNeutroBiLSTM, which incorporates the neutrosophic representation, CNN-based feature extraction, BiLSTM-based sequential modeling, and the indeterminacy representation based on the Sobel operator, has been found to outperform all the other architectures:

- **Test Accuracy:** 92.92%
- **F1-score:** 0.9322
- **AUC:** 0.998214
- **CAR:** 0.9349
- **ECE:** 0.0456

In comparison with the baseline convolutional neural network (CNN) model, the proposed model shows an accuracy improvement of around 5.0% and an F1-score improvement of around 5.6% during the test phase.
The improvement in the performance of the proposed model can mainly be attributed to the indeterminacy representation carried out by the Sobel operator, which emphasizes the stroke boundaries and the local gradient changes of the handwritten character images. This emphasis on the transitions of the character structures during the handwriting process helps the network to better deal with the ambiguous character areas through the application of the Sobel operator.
In addition, the more significant improvement observed for the HIJJA dataset compared to the AHCD dataset indicates that the proposed architecture is more effective for handling datasets where there is more handwriting variation.
Overall, the results confirm the effectiveness of the incorporation of uncertainty-aware neutrosophic representation with spatial feature extraction through convolutional neural networks (CNNs) and contextual sequential modeling through bidirectional long short-term memory networks (BiLSTMs) for the effective Arabic handwritten character recognition task.

4.4 Comparative Performance Visualization

Figure 2 illustrates a comparative summary of the performance of the models, including the accuracy, F1 score, and CAR of all models tested on the two datasets.

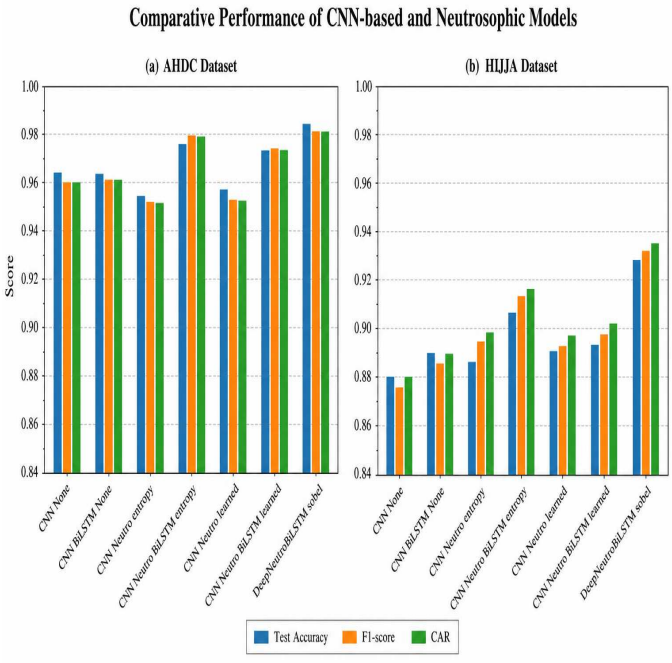


Fig. 2. Comparative Performance of Evaluated Architectures on AHCD and HIJJA.

Figure 2 below offers a comparative visualization of the performance of the architectures that were evaluated on the AHCD and HIJJA datasets. Evaluation on the datasets is carried out on three key metrics: Test Accuracy, F1-score, and CAR.

For the AHCD dataset, all the architectures have high recognition performance due to the relatively high level of structuring within the data. However, improvements are seen when neutrosophic uncertainty modeling and sequential feature learning are employed. Here, CNN-Neutro-BiLSTM models are seen to outperform the baseline CNN models, thereby validating the idea of integrating uncertainty representations with sequential feature learning. Among the models, the proposed DeepNeutroBiLSTM model with the Sobel indeterminacy representation has the highest performance, with a 98.39% accuracy on the test data, a 0.982 F1-score, and a 0.982 CAR.
For the HIJJA dataset with greater variations in handwritings and structural ambiguity, the performance difference between the architectures becomes more prominent. The baseline convolutional neural network (CNN) model achieves an approximate test accuracy of 87.96%. Meanwhile, the performance of the proposed models with the incorporation of neutrosophic representation and sequential learning demonstrates consistent improvement. Once again, the proposed DeepNeutroBiLSTM architecture demonstrates the best performance with an approximate test accuracy of 92.92%, an F1-score of 0.932, and a classification accuracy rate (CAR) of 0.935.
Overall, the comparative visualization has clearly proved that the integration of neutrosophic uncertainty modeling, Sobel-based indeterminacy representation, and BiLSTM sequential learning provides performance improvements over traditional CNN architectures. The results obtained have proved the efficacy of the hybrid approach to the Arabic handwritten character recognition problem, especially when dealing with challenging datasets like HIJJA.

4.5 Ablation Study

In order to understand the impact of individual architectural components, an ablation study was conducted. Starting with the baseline CNN model, the addition of BiLSTM layers was found to provide minimal improvements to the AHCD dataset while providing significant improvements to the HIJJA dataset.
Finally, the entire DeepNeutroBiLSTM model that incorporates the neutrosophic representation method based on the Sobel filter with CNN feature extraction and BLSTM sequential modeling was observed to produce the best performance over both datasets. The findings confirm that the combination of representation learning with uncertainty measures, spatial feature modeling, and sequential modeling is the best approach to Arabic handwritten character recognition.

4.6 Training Dynamics and Convergence Behavior

Figures 3 ,4 ,5 and 6 describe the accuracy and loss curves of the proposed model, named DeepNeutroBiLSTM, on both AHCD and HIJJA datasets during training and validation.
In the training curves shown in Figures 3 and 5, there is rapid convergence during the initial stages of the model's training and then stable optimization during the rest of the epochs. The loss functions for both the training and validation datasets converge smoothly without any divergence. In addition, the fact that there is a small difference between the accuracy of the training and validation datasets shows that the model is not overfitting.
These observations confirm that the proposed architecture of DeepNeutroBiLSTM with indeterminacy representation using Sobel is able to maintain stable training dynamics. In addition, the proposed neutrosophic representation with sequence models does not cause instability during optimization.

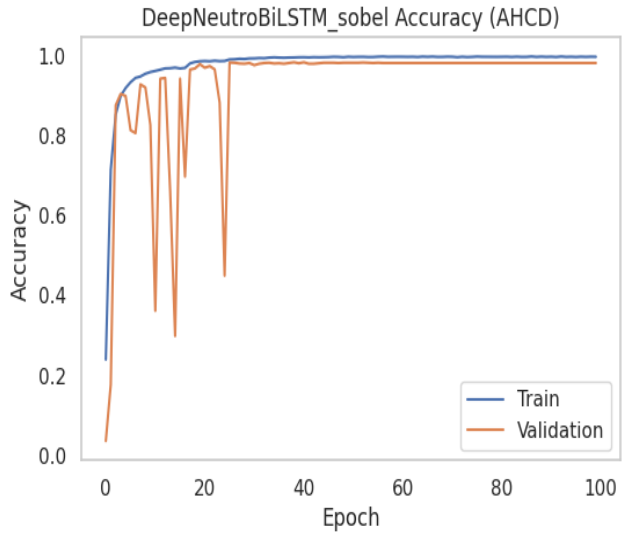


Fig 3:Training and validation accuracy curves of the proposed **DeepNeutroBiLSTM** model with Sobel-based indeterminacy representation on the **AHCD dataset**.

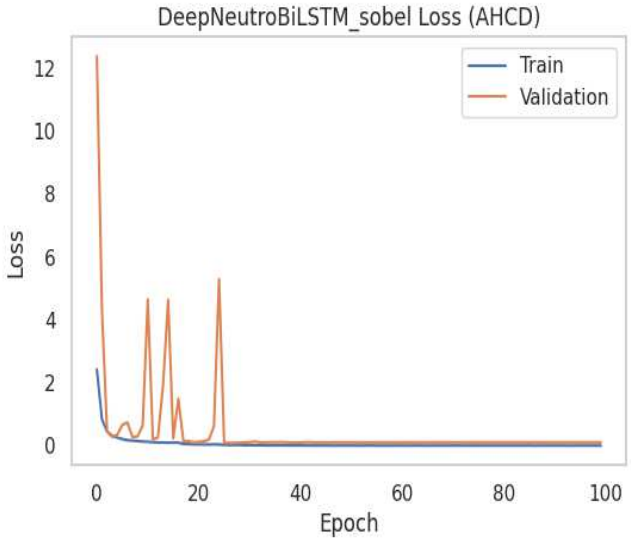


Fig 4. Loss curves of the proposed **DeepNeutroBiLSTM** model with Sobel-based inde-terminacy representation on the **AHCD dataset.**

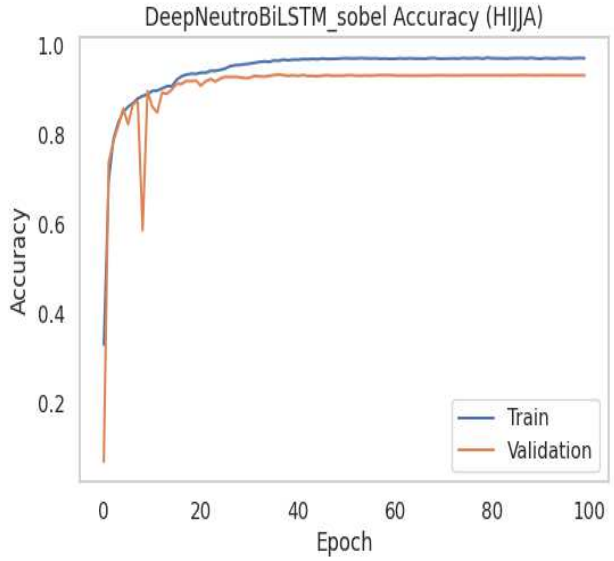


Fig. 5. Training and validation accuracy curves of the proposed **DeepNeutroBiLSTM model with Sobel-based indeterminacy representation** on the **HIJJA dataset**.

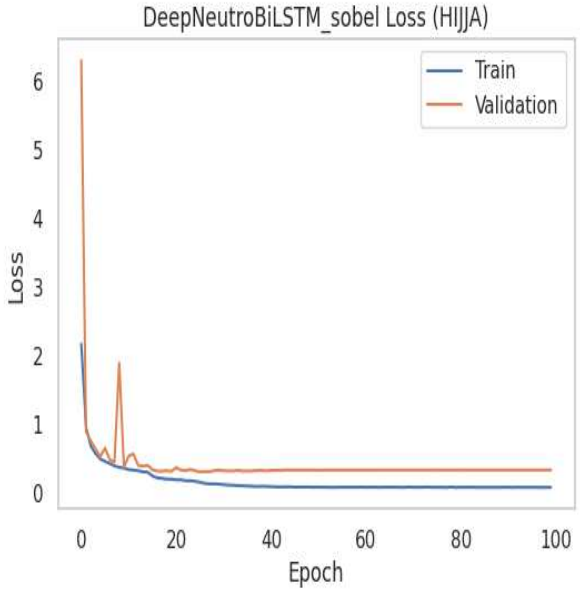


Fig. 6. Loss curves of accuracy curves of the proposed **DeepNeutroBiLSTM** model with Sobel-based indeterminacy representation on the **HIJJA dataset**.

4.7 Error Analysis

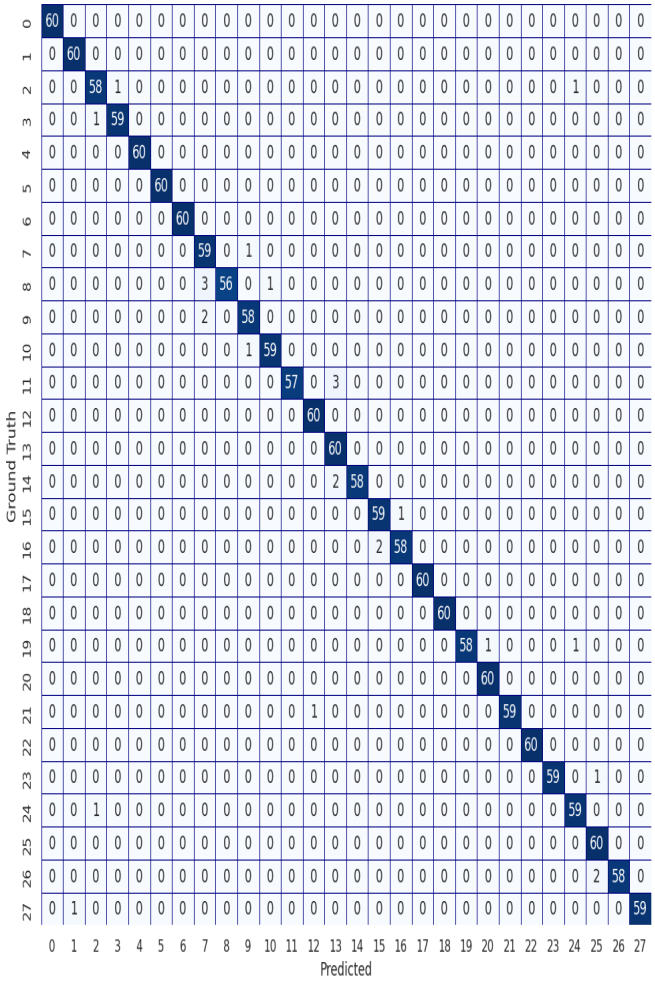


Fig.7. Confusion Matrix of the **DeepNeutroBiLSTM-Sobel Model** on the AHCD Dataset

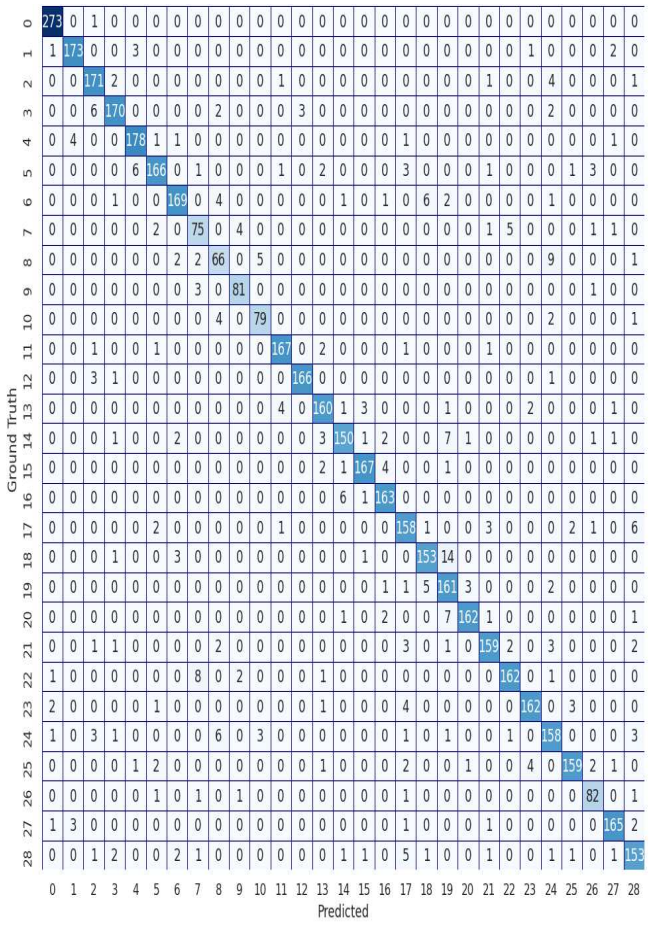


Fig. 8.Confusion Matrix of the **DeepNeutroBiLSTM-Sobel** Model on the HIJJA Dataset

To further analyze the prediction behavior of the proposed model, the confusion matrices for the **AHCD** and **HIJJA** datasets are presented in **Figures7 and 9**, respectively.

For the AHCD dataset (Figure 7), the confusion matrix clearly reflects diagonal dominance, implying that the majority of the character classification has been performed correctly. It is observed that all the classes have close to perfect classification, with the range of correctly classified samples ranging from 58 to 60 per class. Only isolated errors are visible, and these are mostly due to the classification of one or two samples into other visually similar classes. This again reconfirms the high discriminative power of the proposed model, i.e., DeepNeutroBiLSTM with indeterminacy representation using the Sobel operator, to detect the subtle changes in the strokes of the handwritten Arabic characters.

For the HIJJA dataset (Fig. 8), the diagonal elements of the confusion matrix are again prominent, though with a slightly higher occurrence of off-diagonal elements compared to the AHCD dataset. This is as expected due to the higher variability and structural ambiguities present in the HIJJA dataset. There are moderate misclassification rates between visually similar characters that have common stroke patterns or differ slightly in their structural patterns. However, the overall classification accuracy for most of the classes is high, with correct classification rates greater than 150.

In general, the confusion matrices demonstrate that the DeepNeutroBiLSTM model, with the incorporation of the Sobel-based neutrosophic uncertainty modeling, is successful in learning representations for handwritten Arabic characters while maintaining high accuracy.

4.8 Comparison with State-of-the-Art

Table 3. Comparison of the proposed method with state-of-the-art approaches on the AHCD dataset.

To further measure the efficacy of the proposed model architecture, Table X compares the performance of the proposed model with a number of recent CNN-based as well as hybrid CNN-recurrent models from the literature. Most existing models rely on conventional CNNs as well as CNN-LSTM/CNN-BiLSTM architectures for effective spatial as well as sequential feature representation for handwritten characters. In contrast, the proposed model utilizes the concept of neutrosophic uncertainty modeling along with Sobel indeterminacy representation within the CNN-BiLSTM framework. This enables the model to effectively represent the stroke uncertainty as well as contextual dependencies for competitive results on the AHCD as well as HIJJA datasets.

Table 6. Comparison between the proposed DeepNeutro-BiLSTM model and recent CNN-based and CNN-BiLSTM architectures for Arabic handwritten character recognition.

Method	Architecture	Test Acc.	F1	AUC
El-Sawy et al.[35]	CNN	AHCD	94.90	2017
Ullah & Jamjoom[36]	CNN	AHCD	95.15	2022
Bin Durayhim et al.[37]	CNN	AHCD	97.60	2023
Alghyaline et al.[38]	Optimized CNN	AHCD	98.30	2024
Maalej et al.[39]	CNN-BiLSTM-CTC	IFN/ENIT	92.21	2018
Rabi et al.[40]	CNN-BLSTM + GAN augmentation	IFN/ENIT	95.23	2024
Mosbah et al.[41]	CNN-BiLSTM-CTC	IFN/ENIT	98.09	2024
Bounour et al.[42]	CNN-BiLSTM-CTC + Attention	IFN/ENIT	97.84	2025
Ayadi et al.[43]	CNN-LSTM	Arabic handwritten characters	≈96–97	2025
Proposed DeepNeutro-BiLSTM	**Neutrosophic + Sobel + CNN-BiLSTM**	**AHCD / HIJJA**	**98.39 / 92.92**	2026

Conclusion:

This study introduces DeepNeutroBiLSTM, a novel hybrid framework for Arabic handwritten character recognition that utilizes the neutrosophic representation and CNN-BiLSTM architecture. The proposed framework utilizes Sobel-based indeterminacy modeling for the effective recognition of handwritten characters.

The experimental results obtained using the proposed framework on the AHCD and HIJJA datasets showed that the pro-

posed framework performs better than other baseline architectures, including CNN, CNN-BiLSTM, and neutrosophic CNN. The accuracy obtained using the proposed framework was 98.39% for the AHCD dataset and 92.92% for the HIJJA dataset, thereby validating the performance of the proposed framework for handwritten character recognition.

The results obtained in the present study demonstrate that the neutrosophic representation using Sobel-based indeterminacy can significantly improve the recognition of Arabic handwritten characters. The framework proposed in the study can provide an effective solution for handling the variability of handwriting and the noise present in the images. Future work will involve the extension of the framework for Arabic handwritten word and text recognition.

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