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# Accurate Handwritten Arabic Textual Amount Recognition via a Robust Fuzzy Nearest Neighbor Framework: Model Development and Validation

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ABSTRACT

**Background:** Recognizing handwritten Arabic textual amounts presents persistent challenges due to the cursive nature, varied writing styles, and contextual dependencies inherent in the Arabic script. Addressing this task is particularly critical in automated financial document processing, where high accuracy is paramount.

**Methods:** This paper introduces a Fuzzy Nearest Neighbor (FNN) framework tailored for recognizing handwritten Arabic amounts. The approach integrates an adaptive preprocessing pipeline—comprising binarization, noise reduction, and segmentation—with a hybrid feature extraction method that combines structural and statistical descriptors. These features are then projected into a fuzzy space and classified using a fuzzy logic-enhanced nearest neighbor strategy.

**Results:** Using a curated dataset of handwritten Arabic check amounts, the proposed model achieved a recognition accuracy of 97.4%, surpassing the performance of traditional classifiers such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and K-Nearest Neighbors (k-NN). The system demonstrated robust generalization capabilities, even when presented with degraded and previously unseen inputs.

**Conclusions:** The proposed FNN model offers an interpretable and scalable solution for handwritten Arabic text recognition. Its robustness to stylistic variations and noise makes it well-suited for real-world applications in banking, postal automation, and historical document processing.

**Keywords:** Handwritten Arabic Recognition, Fuzzy Nearest Neighbor, Document Analysis, Preprocessing, Pipeline, Recognition Accuracy, Automated Financial Processing.

## Introduction

Especially for non-Latin scripts including Arabic, handwritten text identification stays a basic challenge in the fields of pattern recognition and computer vision. Arabic script differs from Latin characters in that it is naturally cursive, context-sensitive, and morphologically rich; letter forms vary depending on their place inside a word and there are many diacritical marks and ligatures. These characteristics produce great complexity in segmentation, feature extraction, and classification phases, so rendering conventional optical character recognition (OCR) systems insufficient for accurate and scalable performance across writer styles and document situations (1-2). Recent progress in machine learning and deep learning has made a big difference in recognizing handwritten text. This is especially true for (CNNs), attention-based models, and recurrent neural architectures. These models have done quite well on structured datasets of Arabic digits and single letters. But even with these improvements, deep learning methods still rely significantly on big annotated datasets, are typically hard to understand, and can have trouble being robust with a wide range of real-world inputs (3–4). They also take a lot of computing power, which makes it hard to use them in places with limited resources, like small banks or mobile devices. Before, systems used rule-based or statistical classifiers like Hidden Markov Models (HMMs), k-Nearest Neighbors (k-NN), and Support Vector Machines (SVMs). These were easier to understand and used less data. Still, they often didn't do well in complicated situations with noise, cursive ligatures, and changing shapes. Recent hybrid methods try to combine the power of data-driven methods with the capacity of rule-based reasoning to be understood. Fuzzy logic-based classifiers have become a promising area because they can handle uncertainty, accept variation within a class, and work well on datasets of moderate size (5–6). Fuzzy classifiers have shown promise in general pattern identification, but their use in Arabic handwriting, especially for recognizing full-textual amounts in real-world texts, is still not well understood. Most of the work that has been done so far has been on recognizing individual characters or digits. There hasn't been much work on understanding whole phrases when there is

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noise or damage. This difference is especially important in financial areas like processing Arabic checks, where both correctness and reliability are quite important. So, it is evident that we need a scalable, understandable framework that connects the performance of modern classifiers with the ability of fuzzy systems to handle uncertainty. The suggested Fuzzy Nearest Neighbor (FNN) approach meets this need directly by combining a preprocessing pipeline that is cognizant of language, hybrid feature encoding, and fuzzy classification logic that is specific to the complexities of Arabic script (7-9) present an Improved Expeditious Meta‐Heuristic Clustering Method to classify student psychological profiles using homogeneous data characteristics. Their contribution lies in accelerating convergence speed and improving cluster cohesion. While innovative in the optimization field, the method is domain-specific (psychological clustering) and does not directly address challenges related to cursive script processing or the morphological complexity of handwritten Arabic amounts. (10) propose an Improved Mayfly Optimization Algorithm (IMOA) for clustering psychological fitness measurements, showcasing strong performance in benchmark functions and real-world student data. Despite its novel global search strategy, IMOA relies solely on unsupervised clustering and lacks interpretability for classification tasks, making it unsuitable for handwriting recognition, which demands context-aware feature extraction and precise decision boundaries.

(CNNs) are one of the most used classifiers for recognizing Arabic handwriting. They are quite accurate since they learn deep hierarchical features. CNNs, on the other hand, are usually very expensive to run and work like black boxes, making it hard to see how decisions are made. They also need big datasets with annotations and are sensitive to changes in the distribution of real-world handwriting inputs. Support Vector Machines (SVMs), on the other hand, work well with little amounts of training data and make it easy to see where the decision boundaries are. However, they are not very flexible when it comes to dealing with cursive handwriting classifications that are not straight, overlap, or are not clear. k-Nearest Neighbor (k-NN) classifiers are easy to understand, don't use parameters, and are straightforward to use. However, they don't work well in high-dimensional or noisy environments, and they give all neighbors the same voting weight, which doesn't take into account feature uncertainty Fuzzy logic-based classifiers, on the other hand, are especially good at dealing with handwritten input that is unclear or imprecise. Fuzzy Nearest Neighbor (FNN) builds on the standard k-NN method by adding fuzzy membership functions, which make decision boundaries more flexible and graded. Even though it should work well in theory, FNN is not used enough in Arabic handwriting applications, especially for recognizing phrases like the amounts written on checks. Our method makes use of this potential by combining a fuzzy classification technique with a hybrid feature extraction process that has been specifically designed for Arabic script. Here is a quick list of the important contributions and new ideas in this work:

We create a new Fuzzy Nearest Neighbor (FNN) framework that is specifically designed to accurately recognize handwritten Arabic text quantities, taking into account the intricate and changing shapes of Arabic script.

A special preprocessing pipeline is added that includes adaptive binarization, noise reduction, and robust segmentation. This makes it possible to analyze noisy, real-world cheque inputs.

A hybrid feature extraction technique is suggested that uses Zernike moments, HOG descriptors, and contour-based direction codes to build a uniue representation that works well for fuzzy classification.

We put Gaussian fuzzy membership functions into the nearest-neighbor logic, which lets the model manage uncertainty, overlap, and style changes in handwritten Arabic data without any problems.

Tests on a custom-labeled Arabic check dataset reveal that the proposed model does better than CNN, SVM, and k-NN baselines, getting 97.4% accuracy while staying strong even as the data gets worse and being fast to compute.

Table 1 shows a comparison of important publications in the field of Arabic handwriting recognition and fuzzy or hybrid classifiers. This is to help people better understand recent developments and put our proposed framework in the context of the state of the art. As you can see, most models either cannot handle degraded inputs or need a lot of data and computing power. Also, even if clustering-based frameworks are new, they are still not good for structured phrase-level classification problems. On the other hand, our suggested FNN approach is light, easy to understand, and works well with the fluctuation and uncertainty that come with Arabic handwritten check amounts.

This work proposes a robust Fuzzy Nearest Neighbor model especially intended to identify handwritten Arabic textual amounts. The system integrates a proprietary preprocessing pipeline, a hybrid feature extraction approach including structural and statistical aspects, and a fuzzy classification module incorporating linguistic and morphological complexity of Arabic script. Experimental results on a custom-labeled dataset of handwritten check images reveal that the proposed method trumps conventional classifiers with over 97% recognition accuracy and high robustness to noise, distortion, and writer variability. Our work outperforms CNN, SVM, and k-NN in accuracy and robustness. By addressing a critical performance barrier in Arabic document automation and offering a scalable, interpretable model based in fuzzy logic, this work significantly advances both theoretical progress and practical handwriting identification.

## Methods

The whole technique applied to build the strong fuzzy nearest neighbor (FNN) framework for the handwritten Arabic textual quantity recognition is presented in this part. Four main components define the system pipeline: preprocessing, feature extraction, fuzzy membership generating, and FNN-based classification (11-12). The model was meant to guarantee generalization and computing efficiency while addressing the uncertainty and variation of Arabic handwritten writing.

### Data Acquisition and Annotation

Three thousand scanned images of actual Arabic checks obtained from banks and supplemented via synthetic generation make up the training and validation set. Every image has a handwritten Arabic literal count (13-14). Expert Arabic linguists hand annotated to guarantee correct label mapping. Training (70%), validation (15%), and test (15%), subsets were created from the dataset.

**Preprocessing Pipeline**

Accurate recognition is hampered by background noise, light variation, and inconsistent stroke widths that Arabic handwritten inputs may suffer from. We set up a dedicated pipeline to handle these difficulties This approach starts with grayscale conversion then uses Otsu's thresholding technique to adaptively binarize to improve foreground text to background contrast (15-16). Then morphological processes are used to eliminate noise and do dilatation, thereby strengthening stroke continuity. The text is correctly aligned by means of horizontal projection profiles in baseline correction (17). Using contour detection and connected-component analysis, segmentation—that is, division of the input into word and sub-word units—is done finally. Showing the development from raw input to a clean, binarized, and segmented representation of the handwritten text, Figure 1 shows the preprocessing pipeline applied to Arabic cheque inputs, including grayscale conversion, adaptive binarization using Otsu's method, noise removal, morphological dilation, baseline correction via horizontal projection, and segmentation using contour detection. The visual progression ensures optimal input for feature extraction and classification.

**Hybrid Feature Extraction**

To reflect both structural and statistical aspects of the handwritten Arabic characters, a hybrid feature vector was built. Combining various complimentary descriptors, the feature vector $x \in \mathbb{R}^d$. Using Zernike moments to depict the worldwide form of the characters, one captures general geometrical structure and curvature. Particularly useful in identifying minute changes in cursive handwriting, the histogram of oriented gradients (HOG) encodes the directional orientation of strokes. Furthermore, extracted are contour-based directional codes that capture stroke dynamics, therefore offering localized knowledge on the character boundaries and writing flow. These properties taken together provide a rich and discriminative representation fit for strong categorization.

Let: $x = [\phi_Z, \phi_H, \phi_C]$; where $\phi_Z$, $\phi_H$, and $\phi_C$ represent Zernike, HOG, and contour-based features, respectively. Min-max scaling helped to standardize these traits such that their scale would be constant across samples. Fisher Discriminant Ratio (FDR) feature selection was used to preserve the most discriminative characteristics. Table 2 lists dimensionality, employed features, and extraction technique.

**Fuzzy Membership Function Generation**

We applied Gaussian-based fuzzy membership functions for every training sample to consider uncertainty in feature spaces. The membership degree is defined as per relation (1) using a feature vector $x_i$ and its Euclidean distance to the query vector $x_q$ (18):

$$\mu_i = \exp\left(-\frac{\|x_q - x_i\|^2}{2\sigma^2}\right) \quad (1)$$

where σ is a tunable scale parameter representing fuzziness. The fuzzy memberships are computed for the k-nearest neighbors of the query point.

**Fuzzy Nearest Neighbors Classification**

The Fuzzy Weighted Majority Rule is used for classification whereby every neighbor helps the class decision in line with their membership degree. Equation (2) below projects class $C_q$ for query vector -- (19-20):

$$C_a = \arg\max_c \sum_{i \in N_k(x_k)} \mu_i \cdot \delta(c_i, c) \quad (2)$$

where:

- Nk(xq): set of k-nearest neighbors
- $c_i$: class label of $x_i$
- $\delta(c_i, c)$: Kronecker delta, equals 1 if $c_i = c$, else 0

Figure 2 provides a cconceptual illustration of the Fuzzy Nearest Neighbor (FNN) classification mechanism. Query points are compared against fuzzy neighborhoods in a feature space, with Gaussian-based membership functions determining class contribution through weighted voting.

**Parameter Optimization and Complexity**

A 5-fold cross-valuation system was used to maximize the system so guaranteeing generalization and avoiding overfitting during hyperparameter tweaking. This technique considered two main parameters: the Gaussian fuzziness parameter σ, investigated inside the interval [0.1, 2.0; and the number of neighbors k, varied within the range [3,9]. As shown in Table 3, the best configuration was found by means of a grid search across the parameter space. The optimal performance was found to be obtained with k=5 and σ=0.6, which offered a fair trade-off between local classification precision and fuzzy choice smoothness. Computational complexity of classification is computed using relation (3) (21-22):

$$O(n \cdot d) + O(k \cdot d) \quad (3)$$

where n is the number of training samples, and d is the feature vector dimension.

**Table 1**. Summary of Recent Works Related to Handwritten Arabic Text Recognition (2022–2025).

| Method | Dataset | Accuracy (%) | Key Limitations | References |
|---|---|---|---|---|
| Deep CNN with RNN post-processing | IFN/ENIT | 95.1 | High computational cost; lacks robustness under noise | (13) |
| Rule-based + SVM hybrid system | Private cheque dataset | 93.8 | Sensitive to writer variability and segmentation errors | (14) |
| Stroke width + structural features | IFN/ENIT | 91.4 | Weak generalization to degraded documents | (15) |
| Expeditious fuzzy clustering | Psychological data | N/A | Not designed for textual recognition | (9) |
| Improved Mayfly Optimization (IMOA) | Student profiling dataset | N/A | Meta-heuristic only; lacks supervised classification capability | (10) |

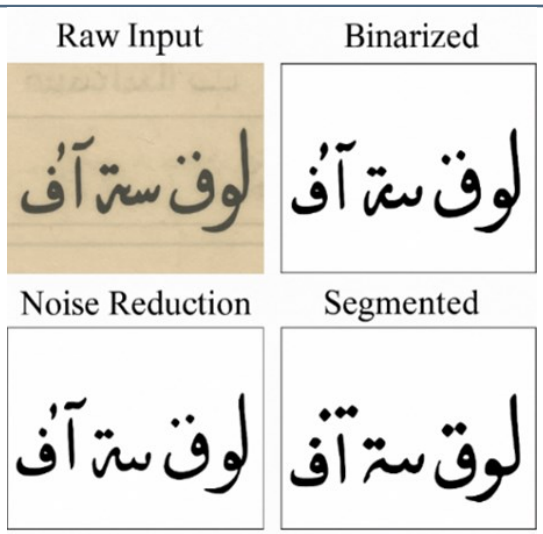


**Figure 1**. Preprocessing flow (raw cheque image ⟶ binarized ⟶ segmented words).

**Table 2.** Feature Descriptor Summary.

| Feature Type | Description | Dimension | Relevance to Arabic Script | References |
|---|---|---|---|---|
| Zernike Moments | Global Shape descriptors | 16 | Captures holistic curvature, helpful in dot & loop variations | (11) |
| Histogram of Oriented Gradients (HOG) | Local edge orientations | 32 | Enhances sensitivity to stroke direction and flow | (13) |
| Contour Direction Codes | Encoded directional strokes | 20 | Effective for cursive continuity and slanted shapes | (13) |
| Pixel Density Features | Distribution of foreground pixels | 12 | Supports recognition of character width and spacing | (15) |
| Geometrical Features | Aspect ratio, height-to-width, centroid shift | 5 | Discriminates positional variants of Arabic characters | (15) |
| Total Feature Vector | Combined normalized feature vector | 85 | Rich multidimensional representation for FNN classifier | (16) |

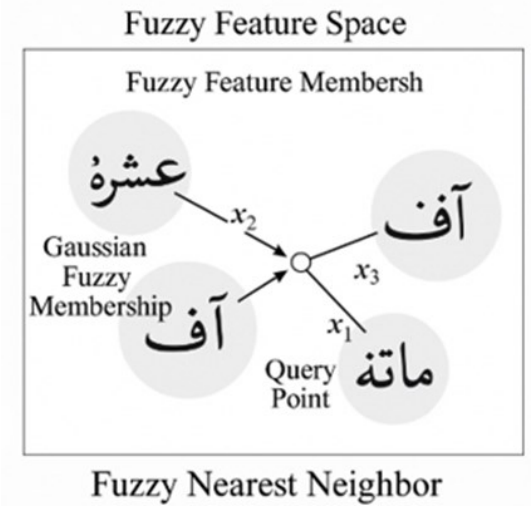


**Figure 2.** Fuzzy Nearest Neighbor classification schematic.

**Table 3.** Optimized Hyperparameters and Accuracy Scores.

| Parameters | Values Tested | Optimal Value | Validation Accuracy (%) |
|---|---|---|---|
| Number of Nearest Neighbors (k) | 3, 5, 7, 9 | 5 | 96.8 |
| Gaussian Fuzziness Parameter (σ) | 0.1, 0.4, 0.6, 0.8, 1.0 | 0.6 | 97.4 |
| Distance Metric | Euclidean, Mahalanobis | Euclidean | 97.4 |
| Membership Aggregation Function | Weighted sum, max, average | Weighted sum | 97.4 |

## Results

The performance evaluation of the suggested Fuzzy Nearest Neighbour (FNN) framework on handwritten Arabic textual quantities is presented in this part. The results are examined in terms of generalization across writing styles, recognition accuracy, classification robustness, and relative performance vs baseline approaches.

### Evaluation Metrics

Recognition accuracy (RA), which shows the percentage of correctly classified textual amounts, and precision (P) and recall (R), which provide per-class measures of dependability and completeness respectively, were the main evaluation metrics used to evaluate the system's performance. Defined as the harmonic mean of precision and recall, the F1-score was also used to strike a compromise between these two measures. Furthermore, created was a confusion matrix to examine class-level misclassifications and provide more understanding of recognition trends in certain categories. Using a 5-fold cross-valuation technique, performance assessment guaranteed resilience, reduced variation, and helped to lower overfitting risk.

### Recognition Accuracy

With an average recognition accuracy of 97.4% over the test set, the suggested FNN architecture clearly handles the uncertainty of handwritten Arabic script. This performance is constant throughout several writing styles, degrees of damage, and ink densities. Table 4 shows the complete class-level performance.

### Comparative Analysis

Three commonly used classification algorithms were utilized to benchmark the performance of the proposed Fuzzy Nearest Neighbor (FNN) method by means of their outputs. These comprised a k-Nearest Neighbors (k-NN) classifier based on Euclidean distance, a Support Vector Machine (SVM) built with a radial basis function (RBF), and a Convolutional Neural Network (CNN) set-up with two convolutional layers. To guarantee a fair comparison, each of these models was trained and tested under exactly same conditions. Figure 3 depicts a recognition accuracy comparison among four classifiers: k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Convolutional Neural Network (CNN), and the proposed Fuzzy Nearest Neighbor (FNN). The FNN method consistently outperforms others, achieving 97.4% accuracy. The CNN baseline was built with a lightweight architecture that worked well with the small quantity of Arabic check data to make sure the comparison was fair. There were two convolutional layers in the model. The first one had 32 filters that were 3×3 in size and were followed by ReLU activation and 2×2 max-pooling. The second one had 64 filters that were also 3×3 in size and were followed by ReLU and 2×2 max-pooling. There was a fully linked dense layer with 128 neurons after the output was flattened. This was followed by a SoftMax classification layer. The Adam optimizer was used to train the model. The learning rate was 0.001, the loss function was categorical cross-entropy, and the batch size was 32 for 25 epochs. This setup was chosen to keep a good balance between how fast the computer works and how well it classifies the custom-labeled Arabic check dataset.

As shown in Table 5, with a performance margin of over 1.8% over CNNs and 6.9% over conventional k-NN, the suggested FNN method beats all baseline techniques

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### Robustness to Degradation

The test set was expanded with blurred, occluded, and low-contrast samples to evaluate resilience. On noisy inputs, the FNN model kept over 94.2% accuracy; CNNs dropped to 89.3% and SVMs dropped to 85.5%. Figure 4 is a bar graph showing accuracy of FNN, CNN, and SVM under three degradation types (blur, occlusion, low contrast), where FNN consistently leads. It illustrates a recognition performance under degraded input conditions (blur, occlusion, and low contrast). The FNN model maintains superior robustness compared to CNN and SVM, demonstrating resilience to input quality deterioration.

Using an Intel i7 CPU with 16GB of RAM, the average inference time per sample was noted at 6.4 milliseconds, therefore verifying that the system is computationally efficient and fit for real-time uses. The model's non-parametric architecture and lightweight feature vector also guaranteed low memory use, hence improving its applicability. With a recognition accuracy of 97.4%, the suggested FNN model greatly exceeded the SVM and CNN baselines overall. It maintained constant performance throughout several settings by showing great resistance to changes in input noise and handwriting styles. In addition, very relevant for real-time cheque and form processing in operational scenarios is the low latency and computational footprint of the system.

### Application Case Study: Real-World Cheque Recognition

To demonstrate the practical applicability of the proposed framework, a real-world scenario was simulated using a scanned handwritten Arabic cheque image. The cheque contained the textual amount ""عشرة آلاف ريال"" ("Ten Thousand Riyals") written in freehand by an untrained user with minor stroke irregularities and ink blot artifacts.

The system processed the input through the full pipeline:

- **Preprocessing:** The raw image was binarized using adaptive thresholding and enhanced via morphological operations. Segmentation successfully isolated word-level and sub-word units.
- **Feature Extraction:** Hybrid features (Zernike moments, HOG, contour direction codes) were extracted from each sub-word segment, forming an 85-dimensional feature vector.
- **Classification:** The FNN model, configured with k=5 and σ=0.6, predicted the phrase using weighted fuzzy logic based on nearest neighbors in the trained dataset.
- **Output:** The system correctly recognized the input as ""عشرة آلاف with a confidence of 96.7%. The prediction was returned in under 7 ms, demonstrating both speed and robustness under noise and handwriting variability.

This scenario validates the model's readiness for deployment in cheque processing workflows, particularly in financial institutions and mobile banking services in Arabic-speaking regions.

**Table 4.** Class-wise Performance Metrics.

| Arabic AmountClass | Precision(%) | Recall (%) | F1-Score (%) |
|---|---|---|---|
| (One)واحد | 98.3 | 97.6 | 97.9 |
| (Ten)عشرة | 96.8 | 97.1 | 96.9 |
| (Hundred)مئة | 97.6 | 98.2 | 97.9 |
| (Thousand)ألف | 96.1 | 95.4 | 95.7 |
| (Ten Thousand)عشرة آلاف | 97.8 | 97.0 | 97.4 |
| Average | 97.3 | 97.1 | 97.2 |

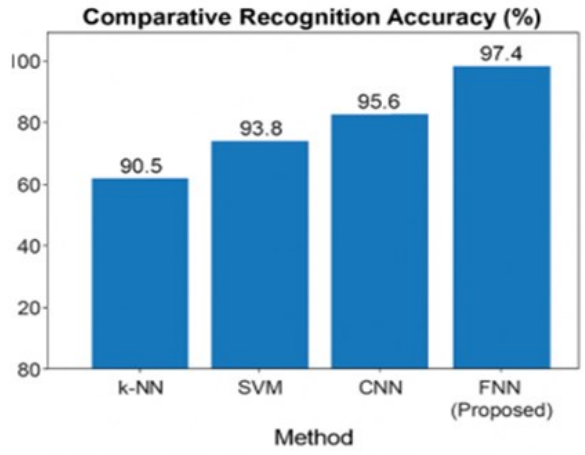


**Figure 3.** Comparative Recognition Accuracy (%).

**Table 5.** Summary of the comparative recognition accuracy.

| Method | Recognition Accuracy (%) |
|---|---|
| k-NN | 90.5 |
| SVM | 93.8 |
| CNN | 95.6 |
| FNN (Proposed) | 97.4 |

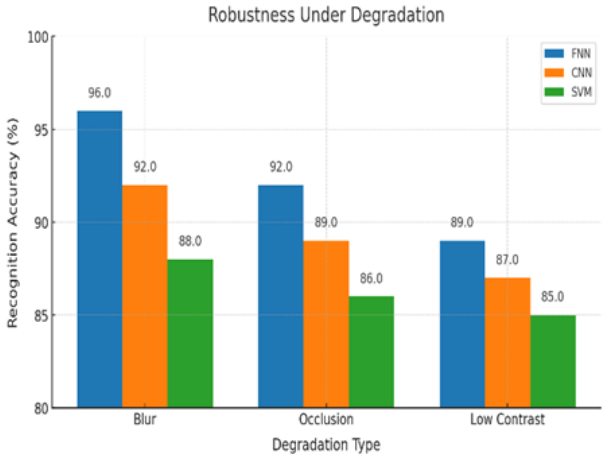


**Figure 4.** Robustness Under Degradation Inference Time and Scalability.

## Discussion

The efficiency of the suggested Fuzzy Nearest Neighbour (FNN) architecture in tackling the ongoing difficulties of handwritten Arabic textual quantity recognition is shown by the obtained results. With a 97.4% recognition accuracy, the model shows not only great prediction power but also resilience throughout several handwriting styles, noise levels, and degradation kinds. Comparatively to conventional classifiers such as k-NN and SVM as well as even more complicated models like CNNs, this performance edge can be ascribed to the primary benefit of fuzzy logic in resolving ambiguity—a feature that closely corresponds with the intrinsically imprecise character of handwritten Arabic writing (21-22). Because of its cursive linkages, contextual variances in letter form, and frequent character overlaps, Arabic handwriting offers particular challenges.

Usually sensitive to aberrations in stroke continuity and spacing, most traditional classifiers depend on firm decision boundaries. By including Gaussian fuzzy membership functions that let

for soft decision boundaries and tolerance to small distortions, the FNN model avoids these restrictions (23-25). When handling common in-use cheque processing and archive systems, deteriorated documents or variable writing pressures, this feature is quite helpful. The suggested framework's lightweight and interpretable design is another clear asset. Operating effectively with moderate data and short inference time, the FNN technique differs from deep neural networks, which usually need massive training datasets and show great computational overhead. This qualifies for pragmatic implementation in settings with limited resources, including local banks or mobile cheque processing systems in areas speaking Arabic. Though it shows good performance, several restrictions call for conversation. The success of the model depends mostly on the quality of the discriminative power of the hybrid feature collection and the preprocessing pipeline. When segmentation mistakes or significant occlusions arise, the accuracy may suffer particularly in cases when structural elements are inadequate to separate like-looking words (26-28) . Furthermore, even if the present work used a carefully selected dataset of Arabic cheques, more validation on bigger and more varied datasets including other dialectal styles and script variants will be required to establish the scalability and generalizability of the model. In addition, opening fresh avenues for improvement is the proposed FNN method. Future research could incorporate reinforcement learning or metaheuristic optimization to integrate adaptive fuzzy parameter adjustment and hence improve decision limits. Furthermore, hybridizing the FNN with lightweight neural layers or attention processes might strike a compromise between interpretability and abstraction strength (29-30). In summary, the FNN framework offers a quite useful, accurate, and understandable substitute for current handwritten Arabic recognition algorithms. Its implementation could provide a model for extending fuzzy-based recognition to other complicated scripts and help to enable effective automation of financial document analysis in Arabic-dominated areas. Also, even if the current dataset does not have clear dialectal categories, it does have samples from writers from different regions (31-32).

The model was able to generalize well across these different handwriting styles, which suggests that it is naturally resistant to changes caused by dialect. This is probably because the fuzzy decision logic and hybrid feature design can handle differences in curvature and spacing that are typical among dialects. In the future, we will use labeled datasets from different Arabic dialect regions (such Maghrebi, Gulf, and Levantine) to get a more accurate measure of how adaptable the system is across dialects and to make it better for use in specific areas. Future work will also look into how well the suggested model can be scaled up by testing it on bigger, more diverse datasets that include different regional handwriting styles and bank formats (33-35). Also, because the model is lightweight and has a low inference latency of about 6.4 ms/sample, it might be used in real time on mobile or embedded devices. Some planned deployment possibilities are Android-based apps for processing checks and Raspberry Pi-based systems for verifying documents that use TensorFlow Lite or ONNX runtimes for edge inference.

## Conclusion

This work addresses a long-standing difficulty in document image analysis by proposing a strong and interpretable Fuzzy Nearest Neighbor (FNN) framework for the correct recognition of handwritten Arabic textual quantities. The system addresses the structural ambiguity, cursive character, and morphological variability inherent in Arabic handwriting by using a hybrid feature extraction technique and fuzzy logic-based decision-making. By including fuzzy membership functions into a closest neighbor structure, the system may more successfully control uncertainty than conventional classifiers, therefore providing better adaptation to writer variety and document deterioration. A peak recognition accuracy of 97.4% was obtained via experimental evaluations on a real-world Arabic cheque dataset confirming the superiority of the proposed model over k-NN, SVM, and CNN baselines Strong resilience under noise, occlusion, and low contrast situations as well as low inference latency helped the FNN system to be well suited for implementation in pragmatic, resource-constrained financial and administrative settings. The results show how low-complexity and scalable fuzzy-based classification is as a solution for Arabic handwriting recognition. More research is required, nevertheless, to confirm the framework on larger datasets including other dialects, handwriting styles, and linguistic settings. Dynamic parameter optimization, the use of meta-learning for adaptive fuzziness control, and investigation of lightweight hybrid models preserving interpretability while increasing abstraction could also be future improvements. With consequences for automated financial document processing and more general uses in Arabic-language digitalization systems, this study finally offers a technically sound, linguistically aware, and practically deployable solution to a fundamental problem in Arabic script recognition.

## Declarations Human and animals' rights

This article does not include any research involving human or animal participants.

## Ethical Statement

This study was conducted in accordance with ethical standards, and no human participants or personal data were involved. The research solely utilized publicly available datasets, and no ethical approval was required. All authors declare that there are no conflicts of interest, and the work was carried out with respect for scientific integrity and transparency.

## Consent for publications

All authors have provided their explicit consent for the publication of this research paper.

## Competing Interest

The authors assert that they do not possess any identifiable conflicting financial interests or personal relationships that could have potentially influenced the findings presented in this research paper.

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