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Design and evaluation of two proposed techniques using DCT and LBP for Arabic "Kana Group" classification and recognition in digital images

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ABSTRACT

The article presents a detailed examination of two different algorithms designed to recognize the Arabic "Kana Group" of words in digital images, employing different feature extraction techniques: Local Binary Patterns and Principal Component Analysis (LBP-PCA) and Discrete Cosine Transform (DCT). The results obtained after testing all models trained using the proposed methods showcased the same classification quality metrics. Our findings demonstrate that the two proposed models yielded high classification quality metrics exceeding 98% for all criteria, including precision, TPR, accuracy, F1-score, thereby confirming the models' reliability for accurate and rapid recognition. While DCT outperformed LBP in most categories, all evaluation indicators for the word recognition accuracy were 100%, except for the term "اضحى ", which was erroneously classified as "امسى "at 8%. This lowered DCT's performance relative to LBP in this case, accounting for the overall diminished accuracy of the metric values for this technique.

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1. Introduction

Understanding Arabic text and words is an intricate problem that integrates the fields of image processing, computer vision, and artificial intelligence technology. This is because of the unique features of the Arabic script due to the letter's cursive nature, the letter formation, and its dependency on spatial context within a word [1]. Moreover, improvements in these areas will enhance the accuracy and capabilities of Arabic recognition systems, thereby introducing opportunities for innovation [2]. Unlike other languages that use the Latin script or other international alphabets, Arabic's unique characteristics pose difficulties in visual assessment of the text [3]. This concern becomes more pronounced when specific linguistic features within grammar and pedagogy, such as the "Kana Group". This group consists of specific verbs pivotal to altering the inflection of nominal sentences in Arabic. The significance of the "Kana Group" lies in its necessity in constructing basic sentence patterns for non-native Arabic speakers.

For this reason, recognizing the importance of constructing a smart system able to automatically identify these actions in texts, as well as in digital images (books, boards, and scanned sites), contributes greatly towards enhancing intelligent educational tools and visually augmenting the applications of analyzing the Arabic language [4]. The accurate identification of Arabic phrases like "Kana Group" poses challenges within computer vision. This is

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primarily because of the intricacies involved in the written form of Arabic texts, which demand scrupulous formal preprocessing with respect to letters and their contextual mutations. Furthermore, the existing systems in this area are not equipped with efficient strategies to cover the grammatical analysis of the Arabic texts, leading them to disregard laden lexico-grammatically complex speech sentences with profound structural significance [5,6].
These features are a barrier to automating processes, many scholars have turned their attention to the problem of detection and recognition of words and texts in languages with connectors, polymorphic letters, like Arabic. These studies are concentrated on problems such as recognition, extraction of words from texts and digital images driven by artificial intelligence and machine learning aimed at creating more precise and reliable recognition systems.
Hannad et al. (2015) proposed a local approach for writer identification by classifying fragments of Arabic handwritten images utilizing the Local Binary Patterns (LBP) technique. In their system, each fragment was represented by an LBP histogram, which made it possible to capture relevant distinct textural features for each writer. A collection of 130 writers was used to test the model [7]. Osina et al. (2017) proposed an algorithm for video and image text detection based on a discrete cosine transform (DCT) and a convolutional neural network (CNN). DCT was used for text detection in images from real world environments CNNs [8]. Chandio, Asghar Ali et al. (2022) proposed a model based on CRNN architecture for recognition of connected Urdu texts within natural images without prior text segmentation. The model has three components: a CNN for feature extraction, a RNN for feature decoding, and a CTC layer for outputting text labels of the results. The model was evaluated on a dataset of Urdu words extracted from natural scenes.
The accuracy measures obtained were CRR of 95.75%, WRR of 87.13% and for WRR1F 94.21% [9]. Mutawa, A. M., Allaho, M. Y., & Al-Hajeri, M. published in 2024 a model which was based on deep learning approaches. They merged two deep neural networks into a single architecture. The architecture first applied a ResNet network to extract features from raw images of text, which were then processed by BiLSTM layers and CTC models for sequencing. This model achieved a character error rate (CER) of 13.2% and a word error rate (WER) of 27.31% for the recognition of Arabic handwritten texts [10]. Akoushideh, A. Et Al. (2025) studied recognizing Arabic and Persian texts located in STRI images of Iranian street signs, traffic signs, and on vehicles license plates employing deep learning methods. Their approach was based on a preprocessing phase, text detection using the CRAFT model, and text recognition using the CRNN model. The accuracy of recognition was achieved at 98.6%, while the training error rate after 20 training cycles dropped from 13.90% to 1.40% [11].
As far as the writer's previously conducted studies go, there seems to be a gap concerning the Arabic "Kana Group" detection and recognition which is crucial for research.
Therefore, this study aims to build an intelligent system based on effective and advanced natural language processing techniques to accurately detect, distinguish, and recognize the "Kana Group" in Arabic texts. The system seeks to achieve high grammatical analysis efficiency, which contributes to enhancing the tools for automated Arabic language comprehension.
Recognition of the phrase "Kana Group" forms the crux of an important information processing problem in the fields of computer vision and machine learning, as it enhances the automated comprehension of Arabic texts using image-based techniques. For this purpose, two strategies were used in this study to derive and represent features that facilitate recognition. First, text patterns are captured using LBP, PCA is applied for dimensionality reduction, and the features are processed using neural networks for recognition. The second method of feature extraction employs frequency features and uses DCT to classify these features with neural networks to create a more effective model.

2. Methodology: Identifying words (kana's group) using LBP and DCT techniques

The study of applying image text detection and recognition utilizing LBP and DCT techniques integrated with AI is a crucial area in the disciplines of digital image processing and pattern recognition. These methods are of great importance in areas such as image forgery detection, text analysis, information extraction, handwriting and pattern recognition, and many other applications. They are extremely precise and powerful in feature extraction from text images which aids in efficiently improving the character recognition accuracy of Arabic characters and in the processing and analysis of handwritten Arabic documents [12-14]. The inclusion of deep neural networks with LBP and DCT features boosts performance tremendously and are remarkably useful in digital image processing [15-17]. Image tampering can be assessed by analyzing its textures and spatial frequencies; therefore, untapped potential exists for its use. [18,19]. Their combination can also enhance the effectiveness of face recognition systems under variable lighting and different viewing angles [20].
Extracting phrases such as "Kana Group" from image-based texts is one of the principal problems of text image processing because it assists in meaning comprehension and stylometry evaluation. In advanced technologies, this extends not only to educational software tools but also to systems for digital documentation, thus expanding its scope.

- Tools, Software, and Datasets Applied: In this investigation, a combination of hardware and software was utilized. A Dell laptop with high specifications was the selected piece of hardware, enabling efficient complex processing. In software, MATLAB 2023b was employed, known for its capabilities in artificial intelligence and computer vision. In this case, a dedicated database (uom_kana_grp) [21] was tailored to assess the accuracy of trained neural network models on image retrieval "Kana Group," which is the focus of this study. Gathering data is a crucial part for model training and testing, and in this study, dataset contains images of the words "Kana Group" in different fonts and sizes. The entire database was organized into two primary directories systematically: the first was the training directory which included eight subfolders for different words, each containing one thousand images. The test folder, which also consisted eight subfolders for 250 test images of the 8 words used during training, duplicated in equal proportions.

This specific dataset was chosen in a way that was both useful for training and testing, so that the evaluation conducted on the models' training for the Kana corpus word recognition tasks was clear.

In this case, two additional methods will be incorporated: the first is based on the extraction of patterns with the LBP technique and the PCA dimensionality reduction, while the latter is based on the frequency analysis by means of DCT. For all the above-mentioned techniques, a neural network will be implemented to develop a model that is able to precisely identify the phrases 'Kana Group'.

To describe the two steps taken for this research, a brief description of two concepts, LBP and DCT, will be given.

- Local Binary Patterns (LBP): In estimating optical features, LBP is a very important technique. It stems from the idea that each pixel can be compared with its neighbors and assigned a binary value of either 0 or 1. A value, in this case binary, which describes the local pattern is generated. Using these values, it is possible to construct a matrix which represents an image which will greatly enhance recognition [7]. For Arabic texts, LBP can be used to recover prominent features of the text based on the letters and words that make up the text.

These functionalities may assist in identifying the intricately designed characters as well as aid in resolving issues concerning the font style and image quality [3].

- Discrete Cosine Transform (DCT): It is one of the mathematical transforms that helps in changing the image from the spatial domain to the frequency domain, so the image can now be presented in terms of its cosine coefficients.

This technique is helpful in losing unimportant data for image and video compression, retaining the visuals which really matter [22]. Recognition of texts also DCT is helpful in reducing the stream of data which is to be processed thus making the recognition more efficient. The result obtained from DCT can be the descriptive features of the objects in the digital images.

Shaped features described morphologically are first extracted using local binary pattern and then a PCA, or Principal Component Analysis are applied to reduce the dimensions in a way that removes superfluous features while

increasing speed and efficiency of the computation. The resulting subset is then fed into a neural network with the objective of developing a model that accurately differentiates and recognizes the various words belonging to the "Kana Group".

The training algorithm employing LBP and PCA focuses on capturing relevant local features from the given images and reducing the feature space to improve the performance of the classifier.

With the previously defined methodology, the evolution of the transformed features is fed to a neural network which allows the formation of basic phoneme/syllable recognition. Confirmation is given in the Kana usability group. Recognition is performed at the word level. The steps of this algorithm are:

Training algorithm: Using LBP and PCA with neural network to recognize the "Kana Group"

Input: Training "Kana Group" images.

Output: Training Model (MDL_I).

Steps:

Step1 Training images are randomly split into 80% for training and 20% for validation.

Step2 Feature Extraction Using LBP Technique:

i. Every image is converted into grayscale and resize (64x64).
ii. LBP is performed by using a circular window of radius one to eight to gather features encompassed within this circle. The image is partitioned into 8 x 8 cells, and the LBP features are statistically distributed within each cell to yield 3,776 primary features.
iii. It employs PCA next to reduce the dimensionality of primary features by selecting 50 critical components. This streamlined selected primary features and improved model efficiency because the model complexity was reduced.

Step3 For the training of the neural network a one hidden layer neural network with a small size has thirty cells. It uses the Levenberg-Marquardt method for the training. Determine an accurate model and at this point save the trained model (MDL_I) along with basic parameters of the algorithm, save them together for future testing and evaluation, see Figure (1, A).

Step4 End.

The effectiveness of the model (MDL_I) obtained from the training process will be assessed via the word recognition test for the Kana's group. A set of metrics including primary classification accuracy, other relevant indicators will be put into consideration for evaluation. The testing algorithm evaluates the effectiveness of the model based on its ability to classify and separate words within the Kana's group using features extracted from their images. The testing and evaluation algorithm is the following:

Testing and Evaluation Algorithm: Employing LBP and PCA in conjunction with Neural Network Model MDL_I

Input: MDL_I fitted model with corresponding training hyperparameters and trained model checkpoints.

Output: Tabulated confusion matrix.

Steps:

Step1 Extract LBP and PCA features for every Test image.

Step2 Execute recognition for test images using MDL_I. Classify and predict each test image in relation to its known output label.

Step3 Determine the confusion matrix of the test images which represents the correct and incorrect identifications and classifications for each class.

Step4 Calculate precision (Pr), true positive rate (TPR), accuracy (Acc), and F1- score alongside other relevant ratios to evaluate model performance.

Step5 Result Preservation.

Step6 Conclusion of the Testing Algorithm.

Step7 End.

The second method applies discrete cosine transform (DCT) to image frequency feature extraction. These features are utilized to build a neural network that is capable of word recognition within the "Kana Group." The recognition algorithm for "Kana Group" images stored in designated folders applies DCT for feature extraction and trains a neural network designed to efficiently predict the correct class for each image, as described below:

Training algorithm: Using DCT with neural network to recognize the "Kana Group"

Input: Training kana's group Images.

Output: Training Model (MDL_II).

Steps:

Step1 Data partitioning: Split the data into 80% for training and 20% for validation.

Step2 Feature extraction using DCT:

i. Resize each test images to 64 x 64 pixels.
ii. Convert the image to grayscale and then apply a two-dimensional DCT transform. An 8 x 8 block is used to partition the image and perform a cosine transform. The key information for each block is concentrated in the low frequencies after the transform, retaining the most important information for the block. The resulting blocks are then transformed into a one-dimensional feature vector.

Step3 Neural network training. Create a neural network with a single hidden layer, trainlm: Using the Levenberg-Marquardt algorithm, the classifications are transformed into "one-hot encoding" using the create dummy variable's function, and then decoded back into the original data, see Figure (1, B).

Step4 Saved the obtained trained model (MDL_II) with the important training parameters for later use in the testing and evaluation stage.

Step5 End.

To evaluate the effectiveness of the model (MDL_II) resulting from the training stage, its ability to classify and recognize kana's words is tested using test images. The evaluation process relies on applying a specific testing algorithm to a test dataset, where features are extracted from the images using DCT and used to determine the model's accuracy. The main of testing and evaluation algorithm as follow:

Testing and Evaluation Algorithm: Using DCT with neural network Model (MDL_II) to recognize the "Kana Group"

Input: Load the trained model (MDL_II) and the basic parameters used in the training process, Load the Test images.

Output: Confusion matrix.

Steps:

Step1 Feature extraction using DCT (Discrete Cosine Transform).

Step2 Prediction test image class using DCT features and a neural network model MDL_II.

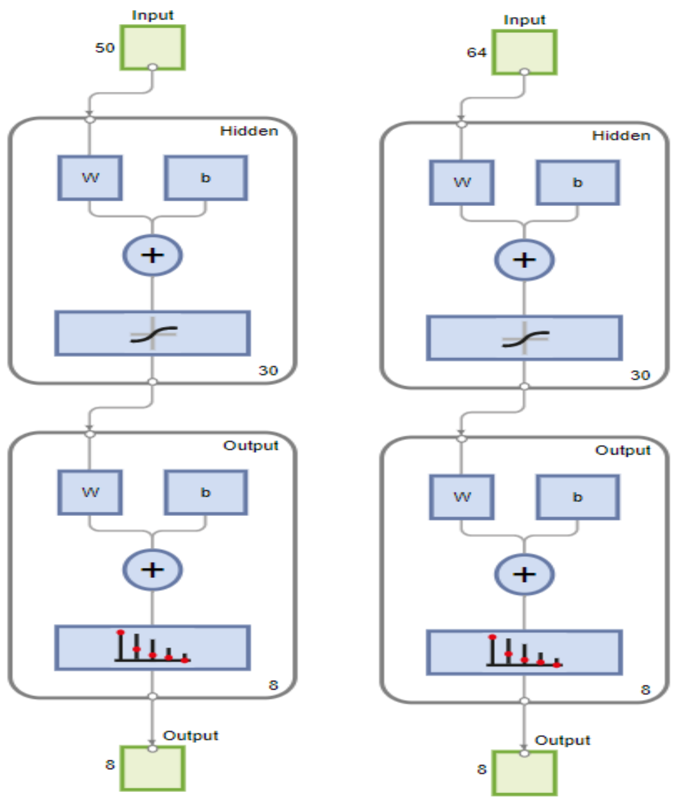
Step3 Drawing and analyzing the confusion matrix.

Step4 Calculating Pr, TPR, Acc, and F1-score.

Step5 Saving results.

Step6 End.

Figure (1) shows the training network diagrams for the two techniques used in this study (LBP-PCA and DCT). Table (1) shows a simple comparison between the two proposed algorithms and the approved models, in terms of feature extraction methodology, final number, and type, with a focus on performance evaluation in terms of speed, noise tolerance, and computational complexity.



A: LBP-PCA technique. B: DCT technique.

Figure 1- the training network diagrams

Table 1- shows the comparison between the two algorithms (LBP-PCA & DCT) and models (MDL_I & MDL_II).

Element	LBP-PCA Algorithm	DCT Algorithm
Extraction Method	Using LBP to extract image texture, then PCA to reduce dimensionality	Using a DCT to extract frequency features from an image
Feature Type	Texture features	Frequency-based features
Dimensionality Reduction	Yes, using Principal Component Analysis (PCA)	No direct dimensionality reduction
Final Number of Features	Depends on the number of PCA components chosen	Mostly constant (e.g., 64 when using an 8×8 DCT)
Speed	Slower due to LBP and PCA calculations	Relatively faster
Discrimination	Powerful at distinguishing between tissue patterns	Useful for images with pronounced spectral differences
Stability against noise	Intermediate	Weak to moderate
Computational complexity	Higher	Less

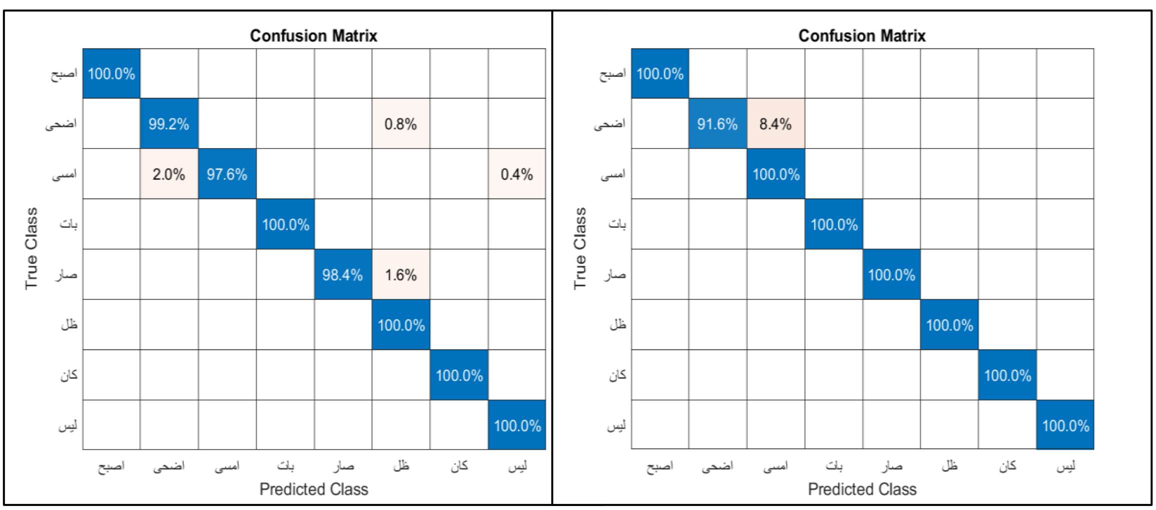
3. Results and Discussions

This section illustrates the results from the experiments designed to assess the effectiveness of the two constructed models for the recognition of words belonging to the class 'kana' in digital images. The first model was constructed with LBP and PCA techniques, and the second model was constructed with DCT. Each model's digital image processing capabilities were trustworthily evaluated on distinct criteria for model relevancy and fidelity using tailored benchmarks. Evaluative performance scoring systems incorporated various aspects of operational quality.

With the proposed models, we were able to assess their capabilities against the images of the 'Kana Group' words through the analysis of a confusion matrix. The assessment was executed with eight classes, each class having a corresponding 'Kana Group' word list which contained 250 images per class, yielding a total of 2000 images. For every model, confusion matrices were generated as shown in the ensuing figures. These matrices depict, in percentage form, the correctly classified values, which are positioned on the main diagonal, and the incorrectly classified values positioned off the diagonal. The results indicate that model (LBP) and model (DCT) performed well above average on both simple and complex category versus category discrimination problems.

Analyzing with the help of a confusion matrix gives valuable information for models' efficiency and helps improve systems to enhance word classification within images.

The performance comparison of the classification models based on LBP (MDL_I) and DCT (MDL_II) was given in Figure (2) through confusion matrices.



A: The confusion matrices using MDL_I model B: The confusion matrices using MDL_II model

Figure 2- the confusion matrices to compare the classification performance of the MDL_I and MDL_II models

As shown in Figure (2), the values indicate the percentage of correct and incorrect predictions for each class using the two proposed techniques. The results showed that most classes were classified with 100% accuracy without any errors, except classes 2, 3, and 5 in the first LBP and PCA model (MOD_I), and class 2 in the second DCT model (MOD_II), where some prediction errors were observed. Using the LBP technique, it is noted that the word "اضحى" was classified correctly with a 99% accuracy rate, while 0.8% of the words were misclassified as "ظل", due to the letter similarity between the two words. As for the word "امسى", it was classified correctly with a 97% accuracy rate, while 2% of the words were misclassified as "اضحى". And 0.4% were misclassified as (ليس). As for the word (صار), there was a slight similarity with the word (ظل), with a misclassification rate of only 0.1%. It is worth noting that the use of the DCT technique resulted in a very high classification accuracy, with a success rate of 100% for all words, except for the word (صار), where 8% of it was misclassified as (امسى). The results clearly indicate that the accuracy of the (MOD_II) model is superior to the (MOD_I) model . demonstrating improved classification performance using the adopted techniques.

The confusion matrices were analyzed, and averages of key metrics were calculated, including: Pr, TPR, Acc, and F1-score, needed to evaluate the models' performance in classifying each class in the test dataset. A comprehensive evaluation of the two models was performed by calculating the overall average of these metrics across all categories classified by each model. This analysis allowed us to measure the accuracy and efficiency of each model in classifying the "Kana Group" words, focusing on identifying the most superior model and revealing the categories that demonstrated difficulty in classification. The results of the metrics extracted from the confusion matrices were compiled and presented in Tables (2 & 3), that providing a thorough comparison of the two models performance based on relevant criteria.

Table 2- Evaluation metrics for each kana's group words category using the LBP and PCA model with overall means

Class	Pr %	TPR%	Acc%	F1-Score%
اصبح	100.00	100.00	100.00	100.00
اضحى	98.02	99.20	99.65	98.61
امسى	100.00	97.60	99.70	98.79
بات	100.00	100.00	100.00	100.00
صار	100.00	98.40	99.80	99.19
ظل	97.66	100.00	99.70	98.81
كان	100.00	100.00	100.00	100.00
ليس	99.60	100.00	99.95	99.80
Overall Quality Metrics	99.41	99.40	99.40	99.40

Table 3- Evaluation metrics for each kana's group words category using the DCT model with overall means

Class	Pr %	TPR%	Acc%	F1-Score%
اصبح	100.00	100.00	100.00	100.00
اضحى	100.00	92.00	98.95	95.62
امسى	92.25	100.00	98.95	95.97
بات	100.00	100.00	100.00	100.00
صار	100.00	100.00	100.00	100.00
ظل	100.00	100.00	100.00	100.00
كان	100.00	100.00	100.00	100.00
ليس	100.00	100.00	100.00	100.00
Overall Quality Metrics	99.03	99.00	98.95	98.95

Table (2) shows that the number of errors in the classification of items was relatively high, but the total values affected by these errors were slight, as the overall classification accuracy ranged between (97.60% - 99.95%). As for Table (3), an error appeared in the classification of the words (امسى) and (اصبح), while the rest of the words achieved a high classification accuracy of 100%. The lowest accuracy recorded was 92.00%. The performance of the improved models using the two techniques adopted in this study (LBP with PCA and DCT) demonstrates a high level of efficiency and accuracy in word classification and recognition of the "Kana Group" within digital images. The results demonstrated that both models can extract and effectively process the intrinsic features of the image, resulting in a significant improvement in word discrimination accuracy. It is worth noting that the DCT-based model outperformed the LBP model, achieving the best results in recognizing the "Kana Group" confirming its effectiveness in accurately representing the characteristics of text images and enhancing its reliability in real-world application environments.

Although the two developed models, based on LBP with PCA and DCT, are efficient in recognizing "Kana Group", there are some limitations that should be taken into account. Some other words in the Arabic language may be similar in form or structure to these words, which could lead to confusion in distinguishing between them with high accuracy. It is worth noting that the two proposed systems are not intended to be a final decision-making tool; rather, they are intended as aids to speed up the search and word recognition process. Therefore, the occurrence of some errors does not affect the overall reliability, as the primary goal is to support researchers and facilitate access to targeted words with minimal effort and time.

4. Conclusions

This study presents a detailed examination of two different algorithms designed to recognize the Arabic "Kana Group" of words in digital images, employing different feature extraction techniques: LBP-PCA and DCT. From the results, the following can be concluded:

- For the first model (LBP and PCA): The model demonstrated high efficiency in recognizing most of the words in the "Kana Group", with evaluation Pr exceeding 97.60%, TPR exceeding 97.60%, Acc exceeding 99.65% and F1-score exceeding 98.61% reflecting the model's good ability to extract textual features from images. However, some words from "Kana Group" were slightly less accurate than others.
- For the second model (DCT): This model outperformed, achieving higher classification accuracy than the first model in most categories. All evaluation indicators were high, reaching 100% for all categories and all criteria except for the words "اضحى" and "امسى", where the word "اضحى" was classified as "امسى " by 8%. This percentage resulted in a lower accuracy of the metric values for this technique compared to the LBP technique.
- We propose applying them together to improve the accuracy and efficiency of recognizing Arabic text phrases in various visual contexts, which will significantly contribute to the development of educational tools and automated systems for understanding the Arabic language.

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