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RESEARCH ARTICLE

Quantum-Inspired Moth Flame Optimizer Enhanced Deep Learning for Automated Rice Variety Classification

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ABSTRACT Automated rice variety detection and classification is a task that includes automatically categorizing and identifying varieties or different types of rice based on different characteristics namely grain texture, shape, color, and size. This process is essential for quality assessment, agricultural management, and research purposes. Deep learning (DL) is a subfield of machine leaching (ML) that focuses on training an artificial neural network (ANN) with multiple layers to learn hierarchical representations of data. Convolutional Neural Network (CNN) was widely applied in image-based tasks such as rice variety detection, as they could efficiently capture visual features and patterns. In this study, we propose an Automated Rice Variety Detection and Classification using Quantum Inspired Moth Flame Optimizer with Deep Learning (ARVDC-QIMFODL) technique. The presented ARVDC-QIMFODL technique focuses on the automated identification and classification of distinct kinds of rice varieties. To accomplish this, the ARVDC-QIMFODL technique uses the Median modified wiener filter (MMWF) technique for the noise removal process. Followed by, the feature extraction process takes place by an improved ShuffleNet model. For rice variety detection and classification, the long short-term memory (LSTM) approach was applied. At last, the QIMFO algorithm-based hyperparameter selection process is performed to optimize the detection results of the LSTM system. The simulation outcome of the ARVDC-QIMFODL method is tested on a rice image dataset. An extensive set of experiments showed the remarkable efficiency of the ARVDC-QIMFODL system over other models.

INDEX TERMS Rice variety, computer vision, deep learning, moth flame optimizer, image processing, quantum computing.

I. INTRODUCTION

Computer vision (CV) and Image processing applications in agriculture are of utmost significance because of their low cost and non-destructive evaluation compared to manual approaches [1]. CV applications depend on image processing presenting benefits compared to conventional approaches relying upon manual work. Classifying or evaluating grains by manual approaches can be costly and takes more time since the human factor is at the forefront. The assessment procedure can vary in manual techniques, as per the experience of the assessment experts [2]. Additionally, quick decision-making

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by manual algorithms is problematic when an evaluation is done on a large scale. Rice is one of the products manufactured in numerous countries and consumed worldwide. Rice can be priced on different variables in the market [3]. Colour, texture, fracture rate, and shape are some of these parameters. After gaining products' digital images, different machine learning (ML) methods are utilized for determining these variables and executing classification. ML methods ensure that enormous volumes of data are examined reliably and quickly [4]. It is significant to utilize such techniques in rice production to enhance the quality of final products and to fulfil food safety criteria in an automatic, cost-effective, non-destructive and efficient way [5].

Currently, ML methods have been successfully implemented for operating classification tasks with more precision [6]. The fundamental ideology is gathering adequate images of products to be processed. This procedure abstracts particular variables regarding the product for enabling classification, like shape, texture, and size [7]. An efficacy of ML is its capability to examine a vast quantity of data [8]. ML approaches were a prevalent way of improving the final performances with the ability to derive many physical features from particular data in rice classification [9].

Deep Learning (DL) is a subset of ML, an idea utilizing artificial neural networks (ANN) using advancing learning abilities in image recognition and object detection [10]. DL methods have a complicated structure since they need high-performance computing resources and a high volume of training data [11]. A deep convolutional neural network (DCNN) related design was devised with a concentration on minimalizing trained errors for enhancing the performance accuracy for classifying three rice groups [12]. The training process was combined with stochastic gradient descent (SGD) structures to evade the issue of heuristics and arrange mechanism variables in smart vision [13]. The existing models do not focus on the hyperparameter selection process which mainly influences the performance of the classification model. Particularly, hyperparameters such as epoch count, batch size, and learning rate selection are essential to attain effectual outcomes. Since the trial and error method for hyperparameter tuning is a tedious and erroneous process, metaheuristic algorithms can be applied.

In this study, we propose an Automated Rice Variety Detection and Classification using Quantum Inspired Moth Flame Optimizer with Deep Learning (ARVDC-QIMFODL) technique. The goal of the presented ARVDC-QIMFODL technique lies in the automated identification and classification of distinct kinds of rice varieties. To accomplish this, the ARVDC-QIMFODL technique uses the Median modified wiener filter (MMWF) technique for the noise removal process. Followed by, the feature extraction process takes place by an improved ShuffleNet model. For rice variety detection and classification, a long short-term memory (LSTM) system was applied. At last, the QIMFO algorithm-based hyperparameter selection process is performed to optimize the detection results of the LSTM algorithm. The simulation outcome of the ARVDC-QIMFODL method is tested on a rice image dataset. In short, the key contributions are given as follows:

- An intelligent MOAOA-FDL technique comprising MMWF-based pre-processing, improved ShuffleNet feature extraction, LSTM-based classification, and QIMFO-based hyperparameter tuning is presented. To the best of our knowledge, the ARVDC-QIMFODL model has never been presented in the literature.
- An enhanced ShuffleNet model is employed to capture discriminative features from rice images, aiding in precise variety identification.
- Hyperparameter optimization of the LSTM model using the QIMFO algorithm using cross-validation helps to boost the predictive outcome of the ARVDC-QIMFODL model for unseen data. This optimization process fine-tunes the LSTM system, resulting in improved detection performance.

II. RELATED WORKS

Khatri et al. [14] used ML methods approaches to categorize wheat seeds. The data has kernels from 3 wheat varieties with 70 elements selected arbitrarily for the experiments. Initially, K-NN, classification RT, and Gaussian NB methods were applied for classification. The outcomes of such methods are associated with the ensemble method of ML. In [15], a CNN classification method related to (self-attention-1D-CNN) for enhancing precision in differentiating crop species utilizing canopy spectral data. Five pre-processing approaches and 3 extraction approaches can be exploited for processing data. Anami et al. [16] aim to devise a DCNN structure for the automatic classification and recognition of different abiotic and biotic paddy crop stress using field imageries. The presented method identifies applications in the emerging decision-supportive system and mobile applications.

Chibhabha et al. [17] present Deep MLP generated features. Furthermore, the study even presents the Majority Voting Ensemble (MVE) method. The approach has been assessed against CNN-created features in addition to other conventional methods. The presented solution executed better than other approaches that include end-wise DL methods. Cui and Tan [18] introduce an improved lightweight DL network method for realizing the precise recognition of disease spots and types. Depending on the RlpNet network method, a rice disease image classifier network is devised, that can be the basic network, along with the YOLOv3 target recognition network method to attain the optimizer of extraction feature link, i.e., downsampling by dilated convolutional and upsampling by transposed convolutional. Ramesh and Vydeki [19] modelled a method with the use of Optimized DNN for the classification and detection of rice leaf diseases. For background removal in pre-processing, the RGB images can be transformed as HSV imageries and depending on the hue and saturation part binary images are derived to be separated as non-diseased and diseased portions.

In [20], the author first organized a large data for rice pest detection by manual screening and Web crawler method depending on the IP102 data. This data was IP_RicePests. The variables trained on the ImageNet data utilizing MobileNet, VGGNet, and ResNet networks are utilized as primary values of the targeted data-trained network for gaining image categorization from the rice pest field. Liu et al. [21] suggested a method for monitoring plant physiological index from multispectral data, a novel technique that depends on ML. Utilizing a drone to derive the absorption coefficient of whole leaf area and plant canopies, this study quantified the impacts of plant physiological indicators like the soil and plant analyser development (SPAD) values, dry matter accumulations, and whole leaf region on the relation between the reflectance spectra.

III. THE PROPOSED MODEL

In this manuscript, we have focused on the design of the ARVDC-QIMFODL approach for the automated identification and classification of rice varieties. The goal of the presented ARVDC-QIMFODL technique lies in the automated identification and classification of distinct kinds of rice varieties. To accomplish this, the ARVDC-QIMFODL technique comprises a set of subprocesses namely MMWF-based preprocessing, improved ShuffleNet feature extraction, LSTM-based classification, and QIMFO-based hyperparameter tuning. Fig. 1 signifies the workflow of the ARVDC-QIMFODL approach.

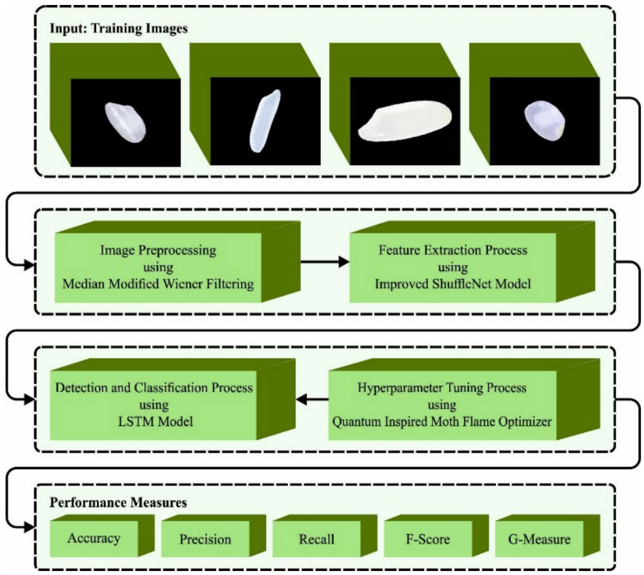

FIGURE 1. Workflow of ARVDC-QIMFODL approach.

A. IMAGE PRE-PROCESSING

The MMWF method is used to eliminate the presence of noise in the image. The aim is to enhance image quality by denoising the background area of the degraded images utilizing the MF [22]. Additionally, this method mainly preserves the edge signal using WFs. Based on WFs, the MMWF method will replace the pixel value of the mask matrix with the median value, thus decreasing the noise from the degraded images. Using the median value $(\tilde{\mu})$, the average value (μ) in the WF can be replaced:

$$b_{\text{mmwf}}(n,m)=\tilde{\mu}+\frac{\sigma^2-\nu^2}{\sigma^2}.\left(a(n,m)-\tilde{\mu}\right) \tag{1}$$

The benefits of the MMWF method are that the image quality of the degraded image was improved as follows: the edge signal is preserved better than using MF and WFs due to the drop-off effects Ultimately, the MMWF method performs better than classical filters regarding the denoising effect; moreover, it removes the background noise signal and preserves the edge signal simultaneously.

B. FEATURE EXTRACTION USING IMPROVED SHUFFLENET

Once the input images are preprocessed, the features are extracted by the use of an improved ShuffleNet model. Squeeze-and-Excitation (SE) block is directly employed to present architecture, due to its flexibility [23]. There are many possible ways where the SE block is embedded as ShuffleNetVl and ShuffleNetV2. The former is the SE-Inside block, where the SE component is positioned inside the ShuffleNet component by directly layering it and then the final convolution layer. Lastly, after the summation (Concat'', "Add'') with the identity branch, SE-Postblock includes the SE units being located. Due to the computation cost, we adopted this strategy aforementioned in all the blocks of the structure (16 overall blocks of ShuffleNetVl and V2), we must integrate a large amount of SE units. Especially, the $H\times W$ spatial dimension of the entire image is shrunk to $z\in\mathbb{R}^c$ by applying a global average pooling function that is a simple aggregation method:

$$z_c=F_{sq}(u_c)=\frac{1}{H\times W}\sum\nolimits_{i=1}^{H}\sum\nolimits_{j=1}^{w}\mathrm{U}_C(i,j) \tag{2}$$

Moreover, in the excitation stage, a bottleneck with two smaller FC layers exploits the aggregated data derived from the squeeze data. The objective is to capture channel-wise dependency and later generate a sequence of per-channel modulation weight. The weight allotted to the input mapping feature was termed feature recalibration, such as the gating modules. The gating model with sigmoid function is applied to achieve these objectives:

$$s=F_{ex}(z,W)=\sigma(g(z,W))=\sigma(W_2\delta(W_1z)) \tag{3}$$

In Eq. (3), δ indicates the ReLU function, $W_1\in\mathbb{R}^{\frac{c}{r}\times C}$ and $W_2\in\mathbb{R}^{C\times\frac{c}{r}}$: indicates a dimensional reduction layer with W_1 parameter with decrease ratio 1, a ReLu and dimensional maximum layer with W_2 parameter. The z descriptor was expressive for the series of channels, particularly weighted. The FC layer and the low-cost channel-wise scaling function are used for rescaling weight for the feature map with the activation function:

$$\tilde{x}_c=F_{scale}(u_c,s_c)=s_c\cdot u_c \tag{4}$$

where $\tilde{X} = [\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_c]$ and $F_{scale}(u_c, s_c)$ signify the channel-wise multiplication between the feature maps $u_c \in \mathbb{R}^{H \times W}$ and the scalar s_c.

The presented model takes all the feature maps afterwards the "concat" process as input and thereby doesn't need to improve the computation cost. Due to the feature refinement, this model improves the learning capability.

C. RICE VARIETY CLASSIFICATION USING LSTM

For the identification and classification of rice varieties, the LSTM model is used. LSTM is a kind of Recurrent Neural Network (RNN) which stores the representation of the newest entries using feedback since they loop feedback [24]. The main concept is to preserve the memory state even after a longer period owing to the existence of memory cells. The memory status existing in every LSTM cell is used to adapt the data value of the prior state based on the prominence of the gating components. The memory status comprises gates that control the flow of data in memory. The typical LSTM includes three layers. The initial layer is the input layer in the LSTM; the recurrent layer is the second layer in the model. Fig. 2 depicts the infrastructure of LSTM. The resultant layer is interconnected to the gating units (forget, input, and output gates).

The conventional equation for LSTM is given below:

$$f_t = \sigma\left(w_f * [h_t - 1, x_t] + b_f\right) \tag{5}$$

$$i_t = \sigma\left(w_i\,[h_t - 1, x_t] + b_i\right) \tag{6}$$

$$\hat{C}_t = tanh\left(w_c \cdot [h_t - 1, x_t] + b_c\right) \tag{7}$$

$$c_t = f_t * C_{t-1} + i_t * \hat{C}_t \tag{8}$$

$$O_t = \sigma\left(W_0 \cdot \left[h_{t-1, x_t}\right] + b_0\right) \tag{9}$$

$$h_t = O_t * tanh\left(c_t\right) \tag{10}$$

where symbol $*$ signifies elementwise multiplication, f_t = forget gate, 6 = sigmoid, h_{t-1} = output of the prior block, W_f = wight, b_f = bias, Xt = input vector, h_t = hidden state C_t = Cell state, and O_t = output gate.

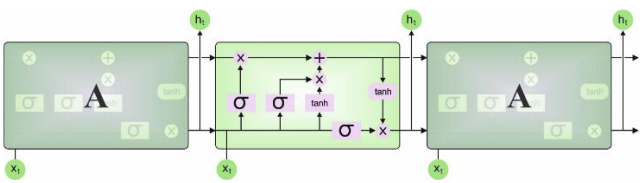

FIGURE 2. LSTM structure.

D. HYPERPARAMETER TUNING USING QIMFO ALGORITHM

For the optimal selection of the hyperparameters related to the LSTM approach, the QIMFO system was used. The hyperparameters tuned are learning rate, epoch size, batch size, and activation function. In quantum computing (QC), the minimum unit for storing data is to be named a qubit (quantum bit). A qubit is a superposition of "1" and "0" states distinguished from a bit (memory cells) in a conventional computer [25]. This can be described as follows:

$$|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{11}$$

In Eq. (11), $|\alpha|^2$ and $|\beta|^2$ denote the probability amplitude of the "0" and the "1" states, and α and β denote two complex numbers. Also, they fulfil the relationship $|\alpha|^2 + |\beta|^2 = 1$.

$$|\phi\rangle = \begin{bmatrix}\alpha \\ \beta\end{bmatrix} = \begin{bmatrix}\cos(\theta) \\ \sin(\theta)\end{bmatrix}, \theta \in [0, 2\pi] \tag{12}$$

Here, the individual quantum moth (QM) was shown in the following:

$$\begin{aligned} QM_i &= (\varphi_1, \varphi_2, \ldots, \varphi_d) \\ &= \begin{pmatrix} cos\,(\theta_{i1}), cos\,(\theta_{i2}), \ldots, cos(\theta_{id}) \\ sin\,(\theta_{i1}), sin\,(\theta_{i2}), \ldots, sin(\theta_{id}) \end{pmatrix} \end{aligned} \tag{13}$$

In Eq. (13), QM_i indicates the setting of i^{th} moths, $\theta_{ij} \in (0, 2\pi)$, $1 \leqq i \leqq n$, $1 \leqq j \leqq d$, n refers to the amount of moths in the group, and d shows the dimension of the quantum bit. All the quantum moths occupy two positions in the searching region, and all the locations represent a solution candidate to the problem that is determined as follows:

$$QM_{ic} = (\cos(\theta_{i1}), \cos(\theta_{i2}), \ldots, \cos(\theta_{id})) \tag{14}$$

$$QM_{is} = (\sin((\theta_{i1}), \sin(\theta_{i2}), \ldots, \sin(\theta_{id})) \tag{15}$$

Step1: Initialization of angle matrix

The problem dimension is dim and the moth population has N individuals. The amplitude probability characterizes the qubit state and it is produced based on the angle matrix. While performing quantum initialization, it is appropriate to define the angle matrix of $N{*}dim$, and the searching space of the angle is 0 to 2π.

$$\theta_{ij} = lb_{ij} + rand\,(0, 1) \cdot \left(ub_{ij} - lb_{ij}\right), 1 \leqq i \leqq n, 1 \leqq j \leqq d \tag{16}$$

In Eq. (16), lb_j and ub_j denote the minimal and maximal limits for the j^{th} dimension of the problem, and $rand(0, 1)$ shows a random integer within [1, 0]. The values of lb_j and ub_j are fixed to 0 and 2π, correspondingly:

$$\theta = \begin{bmatrix} \theta_{11} & \theta_{12} & \ldots & \theta_{1d} \\ \theta_{21} & \theta_{22} & \ldots & \theta_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{n1} & \theta_{n2} & \ldots & \theta_{nd} \end{bmatrix} \tag{17}$$

Step2: Initialize quantum population

QM characterizes a quantum moth matrix comprising N quantum moths, all the quantum moths occupy two locations in the searching region, all the positions signifying a solution candidate to the problem as follows:

$$QM = \begin{bmatrix} QM_1 \\ QM_2 \\ \vdots \\ QM_n \end{bmatrix} = \begin{bmatrix} QM_{1c} \\ QM_{1s} \\ QM_{2c} \\ QM_{2s} \\ \vdots \\ QM_{nc} \\ QM_{ns} \end{bmatrix}$$

$$= \begin{bmatrix} cos(\theta_{11}) & cos(\theta_{12}) & \dots & cos(\theta_{1d}) \\ sin(\theta_{11}) & sin(\theta_{12}) & \dots & sin(\theta_{1d}) \\ cos(\theta_{21}) & cos(\theta_{22}) & \dots & cos(\theta_{2d}) \\ sin(\theta_{21}) & sin(\theta_{22}) & \dots & sin(\theta_{2d}) \\ \vdots & \vdots & \ddots & \vdots \\ cos(\theta_{n1}) & cos(\theta_{n2}) & \dots & cos(\theta_{nd}) \\ sin(\theta_{n1}) & sin(\theta_{n2}) & \dots & sin(\theta_{nd}) \end{bmatrix} \tag{18}$$

After solution space conversion, it is essential to evaluate the fitness value for the individual quality. In QC, the quantum operator manipulates the quantum to change the relative stage of the quantum. The tradeoff between local and global search can be performed by altering the direction and rotation angle of QRG:

$$U\left(\xi\left(\Delta\theta\right)\right) = \begin{bmatrix} cos\left(\xi\left(\Delta\theta\right)\right) & -sin\left(\xi\left(\Delta\theta\right)\right) \\ sin\left(\xi\left(\Delta\theta\right)\right) & cos\left(\xi\left(\Delta\theta\right)\right) \end{bmatrix} \tag{19}$$

In Eq. (19), $\xi(\cdot)$ denotes the function of rotation angle $(\Delta\theta)$ that is defined as follows.

By applying the quantum revolving gate, the new quantum bit can be updated, as given below:

$$\begin{bmatrix} ' \\ \alpha_i \\ \beta_i \end{bmatrix} = U \cdot \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \tag{20}$$

For dynamically updating the angle size and direction, the Differential Evolution (DE) algorithm is used rather than utilizing the fixed angle for the angle rotation of the quantum revolving gate in QIMFO. The procedure to adjust the rotation angle by the DE is shown below:

The rotation angle $\theta_{ij}\left(1 \leqq i \leqq n, 1 \leqq j \leqq d\right)$ in all the quantum moths QM_i is updated by the $DE/rand/1$ strategy using Eq. (21):

$$v_{ij} = \theta_{r_1 j} + F\left(\theta_{r_2 j} - \theta_{r_3 j}\right) \tag{21}$$

where r_1, r_2, and r_3 are random integers within $[1, d]$.

The new angle u_{ij} and the prior angle θ_{ij} are crossed with the specific probability, and the crossover function is given below.

$$u_{ij} = \begin{cases} v_{ij}, & rand \leqq CRorj = randi \\ \theta_{ij}, & else \end{cases} \tag{22}$$

In Eq. (22), CR denotes the crossover probability that is a randomly generated value within [0,1]. $randi$ indicates a random number in the interval $[1, d]$.

$\left|u_{ij} - \theta_{ij}\right|$ denotes the magnitude of the rotation angle. Rotation angle $\xi(\Delta\theta) = S\left(\alpha_i, \beta_i\right) \times \left|u_{ij} - \theta_{ij}\right|$. S signifies the direction of the rotation angle and the updated equation.

$$S\left(\alpha_i, \beta_i\right) = sign\left(\alpha_i \times \beta_i\right) \tag{23}$$

The fitness value was regarded to evaluate the quality level of all the moths. It is essential to convert the solution space of the individual location. Assume that the solution space of the problem definition is $\Omega_{QLSMFO} = [a, b]$, then the conversion equation of solution space is shown as follows:

$$RM_{ic} = \frac{a\left(1 - \alpha_i\right) + b\left(1 + \alpha_i\right)}{2} \tag{24}$$

$$RM_{is} = \frac{a\left(1 - \beta_i\right) + b\left(1 + \beta_i\right)}{2} \tag{25}$$

The QIMFO method grows an FF to obtain a higher efficiency of the classifier. It defines a positive integer to illustrate the superior outcome of the solution candidate. The decline of the classifier error rate is regarded as FF.

$$\begin{aligned} fitness\left(x_i\right) &= Classifier\ Error\ Rate\left(x_i\right) \\ &= \frac{no.of\ misclassified\ instances}{Total\ no.\ of\ instances} * 100 \end{aligned} \tag{26}$$

IV. RESULTS AND DISCUSSION

The rice variety detection outcome of the ARVDC-QIMFODL technique was tested utilizing the rice variety database [10], comprising 5000 samples as shown in Table 1. The size of each image is resized from 256 × 256 to 32 × 32. The names of the five rice varieties are Ipsala, Arborio, Basmati, Yasemin, and Karacadag, acting as classification outputs. The dataset comprises five classes. Fig. 3 displays the sample images.

TABLE 1. Details of database.

Class	No. of Samples
Ipsala	1000
Arborio	1000
Basmati	1000
Yasemin	1000
Karacadagas	1000
Total No. of Samples	5000

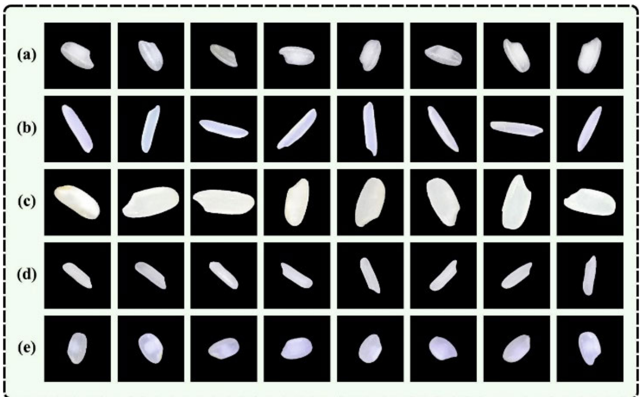

FIGURE 3. Sample Images a) Arborio b) Basmati c) Ipsala d) Jasmine e) Karacadag.

Fig. 4 demonstrates the classifier outcomes of the ARVDC-QIMFODL system under the test database. Figs. 4a-4b depicts the confusion matrix offered by the ARVDC-QIMFODL algorithm on 70:30 of TRP/TSP. The result implied that the ARVDC-QIMFODL methodology has recognized and classified all 5 classes accurately. Besides, Fig. 4c determines the PR curve of the ARVDC-QIMFODL method. The result indicated that the ARVDC-QIMFODL system has achieved higher PR performance under 5 classes.

Lastly, Fig. 4d demonstrates the ROC curve of the ARVDC-QIMFODL system. The outcome exhibited that the ARVDC-QIMFODL approach has led to able outcomes with greater ROC values under 5 classes.

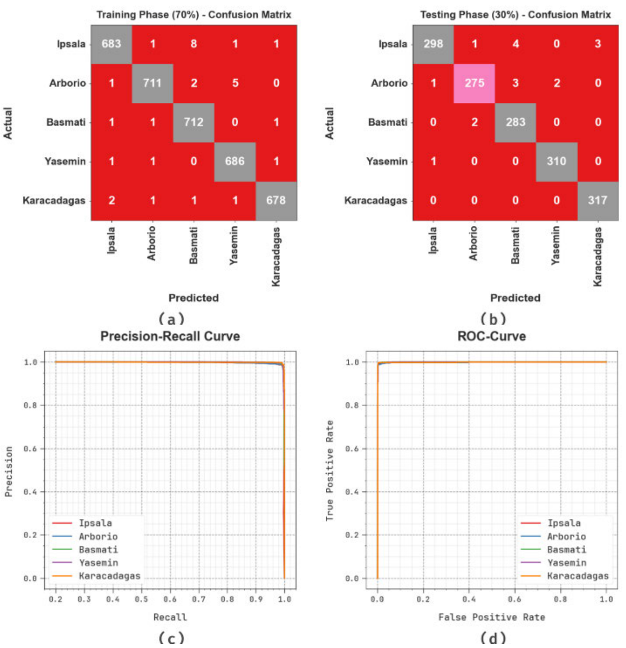

FIGURE 4. Classifier outcome of (a-b) Confusion matrices, (c) PR-curve, and (d) ROC-curve.

The entire rice variety classification outcome of the ARVDC-QIMFODL method is clearly illustrated in Table 2. Fig. 5 demonstrates the brief rice variety detection and classification results of the ARVDC-QIMFODL technique under 70% of TRP. The experimental values inferred that the ARVDC-QIMFODL technique recognizes five rice varieties proficiently. On ipsala class, the ARVDC-QIMFODL technique attains $anaccu_y$ of 99.54%, $prec_n$ of 99.27%, $reca_l$ of 98.41%, F_{score} of 98.84%, and $G_{measure}$ of 98.84%. Meanwhile, in the arborio class, the ARVDC-QIMFODL method accomplishes $accu_y$ of 99.66%, $prec_n$ of 99.44%, $reca_l$ of 98.89%, F_{score} of 99.16%, and $G_{measure}$ of 99.16%. Simultaneously, on basmati class, the ARVDC-QIMFODL system achieves $accu_y$ of 99.60%, $prec_n$ of 98.48%, $reca_l$ of 99.58%, F_{score} of 99.03%, and $G_{measure}$ of 99.03%.

Fig. 6 establishes the brief rice variety detection and classification outcome of the ARVDC-QIMFODL approach under 30% of TSP. The simulation outcome indicated that the ARVDC-QIMFODL system recognizes five rice varieties proficiently. On ipsala class, the ARVDC-QIMFODL method realizes $accu_y$ of 99.33%, $prec_n$ of 99.33%, $reca_l$ of 97.39%, F_{score} of 98.35%, and $G_{measure}$ of 98.35%. In the meantime, on arborio class, the ARVDC-QIMFODL approach reaches $anaccu_y$ of 99.40%, $prec_n$ of 98.92%, $reca_l$ of 97.86%, F_{score} of 98.39%, and $G_{measure}$ of 98.39%. Concurrently, on basmati class, the ARVDC-QIMFODL system achieves $accu_y$ of 99.40%, $prec_n$ of 97.59%, $reca_l$ of 99.30%, F_{score} of 98.43%, and $G_{measure}$ of 98.44%.

TABLE 2. Rice variety classifier outcome of ARVDC-QIMFODL approach on 70:30 of TRP/TSP.

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	$G_{Measure}$
Training Phase (70%)					
Ipsala	99.54	99.27	98.41	98.84	98.84
Arborio	99.66	99.44	98.89	99.16	99.16
Basmati	99.60	98.48	99.58	99.03	99.03
Yasemin	99.71	98.99	99.56	99.28	99.28
Karacadagas	99.77	99.56	99.27	99.41	99.41
Average	99.66	99.15	99.14	99.14	99.15
Testing Phase (30%)					
Ipsala	99.33	99.33	97.39	98.35	98.35
Arborio	99.40	98.92	97.86	98.39	98.39
Basmati	99.40	97.59	99.30	98.43	98.44
Yasemin	99.80	99.36	99.68	99.52	99.52
Karacadagas	99.80	99.06	100.00	99.53	99.53
Average	99.55	98.85	98.85	98.84	98.85

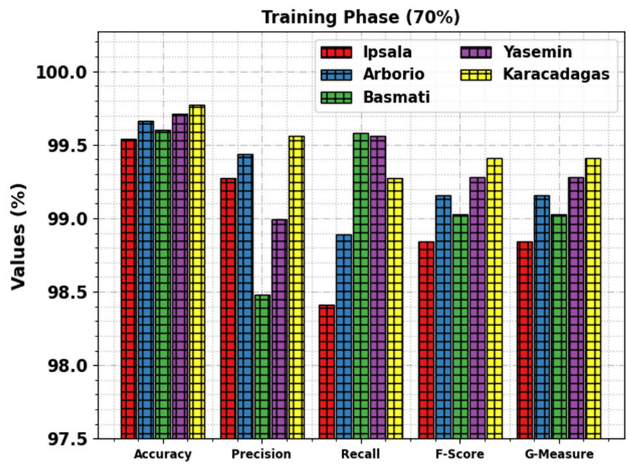

FIGURE 5. Rice variety classifier outcome of ARVDC-QIMFODL approach on 70% of TRP.

Fig. 7 scrutinizes the $accu_y$ of the ARVDC-QIMFODL approach in the training and validation method on the test database. The result stated that the ARVDC-QIMFODL approach gains maximum $accu_y$ values over enhanced epochs. Following, the maximum validation $accu_y$ over training $accu_y$ reveals that the ARVDC-QIMFODL approach gains effectively on the test database.

The loss curve of the ARVDC-QIMFODL algorithm at the time of training and validation is displayed on the test database in Fig. 8. The outcome implied that the ARVDC-QIMFODL approach obtained adjacent values of training and validation loss. It could be clear that the ARVDC-QIMFODL approach achieves capably on the test database.

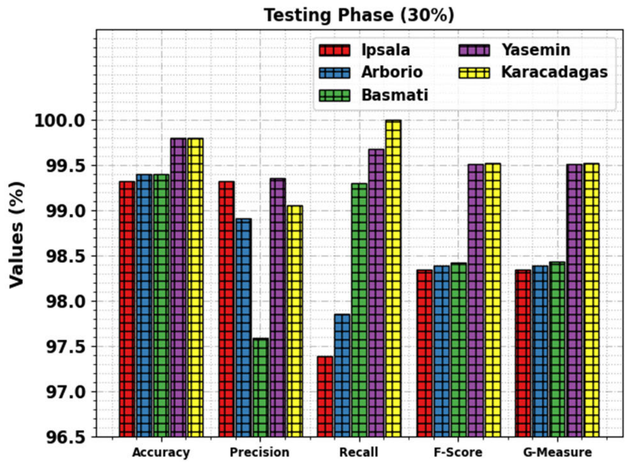

FIGURE 6. Rice variety classifier outcome of ARVDC-QIMFODL approach on 30% of TSP.

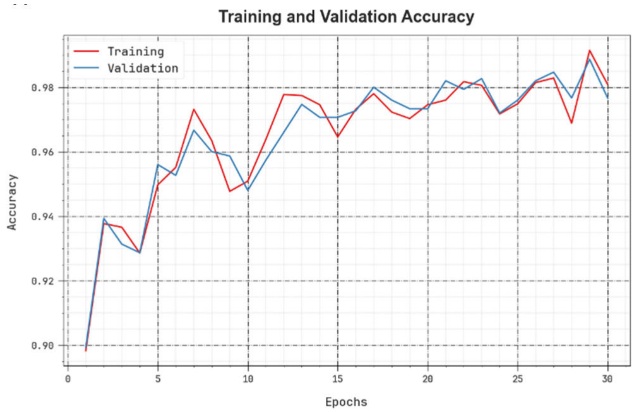

FIGURE 7. $Accu_y$ curve of the ARVDC-QIMFODL system.

FIGURE 8. Loss curve of the ARVDC-QIMFODL system.

To highlight the optimum performance of the ARVDC-QIMFODL approach, a widespread comparison study is made in Table 3 and Fig. 9 [10]. The simulation values illustrated that the ARVDC-QIMFODL technique reaches improved performance over other ones. Based on $accu_y$, the ARVDC-QIMFODL technique attains an increasing $accu_y$ of 99.66% while the CNN-SVM, QNN(Lenet-5), DCNN, CNN(ResNet-50), QNN(Lenet-5), and CNN(VGG16) models obtain decreasing $accu_y$ of 91%, 94.40%, 95.50%, 98.90%, 99.08%, and 99.05% respectively.

TABLE 3. Comparative outcome of ARVDC-QIMFODL approach with other systems [10].

Classifier	Accuracy	Precision	Recall	F-Score
CNN-SVM	91.00	95.27	97.15	96.69
QNN (Lenet-5)	94.40	95.48	97.56	96.87
DCNN	95.50	95.77	96.01	96.73
CNN (Resnet-50)	98.90	96.65	95.20	95.98
QNN (Lenet-5)	99.08	95.68	97.66	96.22
CNN (VGG16)	99.05	96.28	97.43	95.81
ARVDC-QIMFODL	99.66	99.15	99.14	99.14

Meanwhile, concerning $prec_n$, the ARVDC-QIMFODL algorithm gains a higher $prec_n$ of 99.15% while the CNN-SVM, QNN(Lenet-5), DCNN, CNN(ResNet-50), QNN(Lenet-5), and CNN(VGG16) approaches gains reduce $prec_n$ of 95.27%, 95.48%, 95.77%, 96.65%, 95.68%, and 96.28% correspondingly. Moreover, based on $reca_l$, the ARVDC-QIMFODL technique reaches a greater $reca_l$ of 99.14% while the CNN-SVM, QNN(Lenet-5), DCNN, CNN(ResNet-50), QNN(Lenet-5), and CNN(VGG16) approaches gains lesser $reca_l$ of 97.15%, 97.56%, 96.01%, 95.20%, 97.66%, and 97.43% correspondingly.

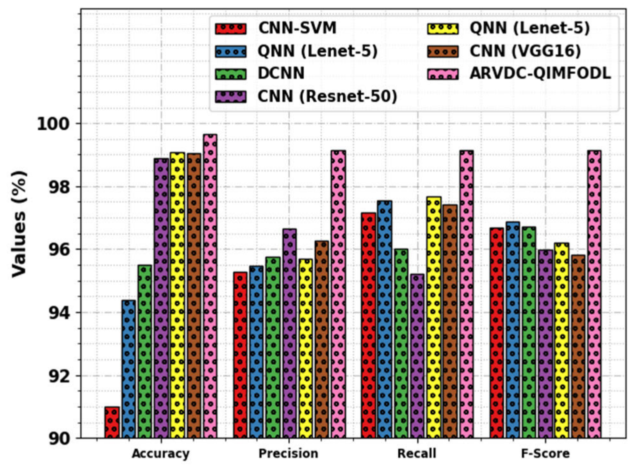

FIGURE 9. Comparative outcome of ARVDC-QIMFODL approach with other systems.

These outcomes displayed the enhanced performance of the ARVDC-QIMFODL system over other existing approaches. The better solution of the ARVDC-QIMFODL approach is because of the combination of the QIMFO-based hyperparameter tuning. Hyperparameters are settings that could not learned in the training method, and then it is set prior to the training model. It has a main effect on the solution of the model, and choosing the better values leads to optimal accuracy. By integrating QIMFO-based hyperparameter tuning, the ARVDC-QIMFODL algorithm attains even optimum outcomes by concentrating on choosing the optimum settings for the method. These performances ensure a better outcome of the ARVDC-QIMFODL methodology with other recent algorithms.

V. CONCLUSION

In this study, we have focused on the design of the ARVDC-QIMFODL method for the automated identification and classification of rice varieties. The goal of the presented ARVDC-QIMFODL technique lies in the automated identification and classification of distinct kinds of rice varieties. To accomplish this, the ARVDC-QIMFODL technique comprises a set of subprocesses namely MMWF-based pre-processing, improved ShuffleNet feature extraction, LSTM-based classification, and QIMFO-based hyperparameter tuning. In this work, the QIMFO algorithm-based hyperparameter selection process is performed to improve the detection results of the LSTM approach. The simulation validation of the ARVDC-QIMFODL technique is tested on a rice image dataset. An extensive set of experiments showed the better performance of the ARVDC-QIMFODL technique over other approaches with an improved accuracy of 99.66%. In future, the detection performance of the ARVDC-QIMFODL system was boosted by feature fusion approaches. In addition, the computation complexity of the proposed model needs to be investigated in future. Besides, the temporal aspect of rice growth can be considered via time-series data, including images captured at various growth stages. It helps to recognize the rice varieties based on their evolving characteristics. Future work can explore ensemble learning techniques that combine multiple DL models to improve classification accuracy and robustness.

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