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Fake-Face Image Classification using Improved Quantum-Inspired Evolutionary-based Feature Selection Method

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***Abstract*—Deep learning models have been quite successful in discriminating synthesized or edited fake-face images. However, in the case of small training data, transfer-learning is rather preferable. This is a complex process for high dimensional feature space due to the curse of dimensionality. To mitigate the same, this paper proposes a new feature selection method for the classification of manually created fake-face images. In the proposed method, a pre-trained deep learning model is used to extract features of an image. Next, an optimal feature subset is selected from the extracted features through an improved quantum-inspired evolutionary algorithm. Lastly, the elicited features are considered to perform the classification. Experiments are conducted on a publicly available manually created fake-face image dataset, namely Real and Fake Face Detection by Yonsei University. The performance of the proposed method is compared with two methods in terms of classification accuracy and the number of selected features. The experimental comparisons exhibit that the proposed method achieves promising results among the considered methods.**

***Index Terms*—Deep Learning, Fake-Face Image Classification, Feature Selection, Quantum-Inspired Evolutionary Algorithm**

I. Introduction

Nowadays, deep learning is the part and parcel of many real-time applications, belonging to the domain of computer vision, data mining, and natural language processing [1]. Recent advancements in these methods have been integrated as image manipulating functionalities in many photo-editing software such as Adobe Photoshop, Snapchat, etc. Such softwares enable a naive person to easily edit or synthesize images either manually or automatically [2]. Moreover, generative adversarial networks (GANs), a category of deep neural models, are able to generate legitimate natural images without human involvement [3]. Although such image manipulating softwares are quite popular among users for entertainment, this may also result in several serious social and security concerns [4], [5] like defamation, authentication, impersonation, hate crimes, frauds, and many others. "DeepFake" [6] is a real-life example of such an image forgery where the face of a victim was swapped with the face of the naked person. Moreover, the determination of such fake images is quite challenging for humans while deep learning methods have been successful for the same [7]. However, for good performance, one of the essential requirements of a deep learning model is the large training data [8] which is rare in case of manually-created fake-face images. In literature, the concept of transfer learning is utilized in the case of small datasets. Hence, this paper tackles the problem of manually-created fake-face image classification with transfer-learning.

In transfer-learning, a pre-trained deep learning model is considered as a feature extractor whose outputs are used as predictor variables for training an image classifier. The trained classifier is then inferred to label the test data. For image classification, AlexNet [9], VGG [10], and ResNet [11] are some of the popular deep neural networks which are available as pre-trained networks. These networks extract high-dimensional features for a wide range of images as they are trained over ImageNet. However, literature has witnessed that when data is of large dimensions, classifiers suffer from the "curse of dimensionality" [12]. The high dimensional data increase the computational complexity immensely which results in making the classifier completely intractable. Moreover, the availability of large datasets for some scenarios might be quiet impossible like manually-created fake face images. In addition, high dimensional data comprises several impertinent and redundant features that degrade classifier efficiency significantly. Therefore, to alleviate the same, feature selection is employed to identify significant features for effective classification.

Generally, feature selection (FS) corresponds to the selection of the optimal or sub-optimal subset of features from a high-dimensional dataset [13] by using certain evaluation criteria. The objective of FS is to improve the classifiers' efficiency by eliminating unimportant features. Further, FS improves the classifier lucidity and addresses the problem of overfitting efficiently by removing the noisy data [14]. However, electing the optimal subset of features from a dataset is an NP-problem [15] as there will be 2^m possible number of feature subsets in a m dimensional feature space. In literature, meta-heuristic algorithms have proven to be quiet reliable for solving complex optimization problems such as data clustering [16]–[18], medical image analysis [19]–[21], and feature selection [22], [23]. Fundamentally, these

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algorithms are mathematical models that are inspired by the optimization behavior of nature [24]–[27]. However, meta-heuristic algorithms generally suffer from the drawback of large processing time which limits their applicability for classification [28]. To mitigate this, quantum-inspired evolutionary algorithm (QIEA) [29] has been a well-accepted meta-heuristic algorithm which merits the process with higher efficiency and low computational time comparatively.

Hung and Casper [30] introduced a quantum state machine for finding the initial value of membership to perform fuzzy clustering for multi-band image segmentation. Wang and Zhu [31] presented a hybrid technique by merging Fuzzy C-Means (FCM) and real-parameter QIEA for identifying the multi-distribution center location. Patel et al. [32] introduced a QIEA based FCM method to alleviate the shortcomings of the FCM [33]. The proposed method finds suitable values for cluster numbers and weighted exponent. Ramos and Vellasco [28] introduced a wrapper-based QIEA to select the optimal features for the classification of EEG data. However, QIEA may trap into local optima and result in bad solution precision. Moreover, this algorithm has rarely been employed for feature selection in image classification, especially for the manually-created fake-face classification.

Therefore, this paper aims at presenting a new improved quantum-inspired evolutionary-based feature selection method (IQIEA-FS) for the classification of manually-created fake-face images. Overall, the proposed method first extracts image features by applying a pre-trained convolution neural network, namely AlexNet [9]. Then, the proposed improved quantum-inspired evolutionary algorithm (IQIEA) is employed to obtain the optimal feature subset from the extracted features. Lastly, the elicited set of features is used to discriminate the images into the real and fake face through a classifier. In this paper, experiments are analyzed on a publicly available manually-created fake-face image dataset, namely Real and Fake Face Detection by Yonsei University [34]. kNN with 10-fold cross-validation is used as the classifier. Moreover, the experimental comparison is performed against two methods, namely AlexNet-kNN and QIEA based feature selection (QIEA-FS), in terms of the number of selected features and classification accuracy. The rest of the paper is arranged as follows: Section II describes the AlexNet along with the quantum-inspired evolutionary algorithm (QIEA) and kNN classifier. The proposed improved IQIEA based feature selection method for fake-face image classification is detailed in Section III. Section IV discusses the experimental analysis followed by the conclusion in Section V.

II. Preliminaries

This section details the AlexNet and quantum-inspired evolutionary algorithm (QIEA).

A. AlexNet

With the advancement in computing capacity and support of graphical processing units (GPUs), convolutional neural networks (CNNs) are becoming deeper and wider. AlexNet

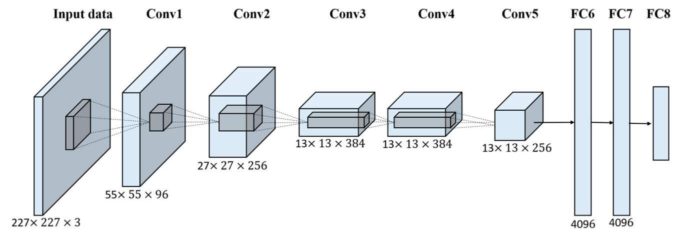

Fig. 1. AlexNet architecture [9]

[9] is a simple and effective architecture of CNN, proposed by krizhevsky et al. at ILSVRC (ImageNet Large-Scale Visual Recognition Challenge) in 2012. It contains cascaded layers, namely five convolutional layers, including pooling and rectified linear unit (ReLU) layer and three fully connected layers. The overall AlexNet architecture is depicted in Fig. 1. ReLU is a half-wave non-linear function which prevents the over-fitting and makes the training process faster.

In this paper, AlexNet is used for feature extraction. The convolution operator of size 3×3 matrix is used as a feature detector in an input image. These features are also known as feature maps. The feature maps are further passed to ReLU function as given in Eq. (1) after each convolutional layer which changes the negative pixel values of the feature maps to zero.

$$r(x) = max(x, 0) \tag{1}$$

Further, the rectified feature maps are passed to max-pooling layer to reduce the dimensionality. In this, a maximum value is taken from a defined window of size 2×2 from the feature maps.

B. Quantum-Inspired Evolutionary Algorithm (QIEA)

Quantum-inspired evolutionary algorithm (QIEA) , proposed by Han and Kim [29], is a popular meta-heuristic algorithm based on the principles of quantum computing (QC). In QC, information is represented in the form of quantum bits (Q) [35]. Each quantum bit is a string of q-bits (q) and is expressed as Eq. (2).

$$Q = (q_1|q_2|\cdots|q_p|\cdots|q_m) \tag{2}$$

where, $p = \{1, 2, \cdots, m\}$ and m corresponds to number of q-bits. Broadly, a q-bit (q_p) is a probabilistic representation that denotes the smallest unit of information. As classical computer bit stores only single information at a time as "0" or "1", a q-bit can represent both "0" or "1" simultaneously by using the concept of probability. Generally, a q-bit (q_p) is a probabilistically linear superposition of "0" and "1" which is defined in Eq. (3).

$$q_p = \alpha_p|\ 0\rangle + \beta_p|1\rangle \tag{3}$$

where, α_p and β_p correspond to two complex numbers that signify the probability of a q-bit to be in the state "0" and state "1" respectively. Thus, according to probability model,

Algorithm 1 Quantum-inspired Evolutionary Algorithm (QIEA)

Initialize N quantum bits, $\{Q_1, Q_2, \cdots, Q_i, \cdots, Q_N\}$. Each Q_i consists of m q-bits, $\{q_1|q_2|\cdots|q_p|\cdots|q_m\}$, where each q_p is $[\alpha_p\ \beta_p]^T$ and is initialized with an assumed value of α_p according to the range defined in Eq. (4) as $\beta_p = \sqrt{1-(\alpha_p)^2}$;
Perform the observation process to generate $P_N^{(t)}$;
Evaluate the fitness of $P_N^{(t)}$;
Store the best solutions among $P_N^{(t)}$ in $B_N^{(t)}$;
Determine the global best solution from $B_N^{(t)}$;
while termination condition does not meet **do**
  Perform the observation process to generate $P_N^{(t)}$;
  Evaluate the fitness of $P_N^{(t)}$;
  Store the best solutions among $B_N^{(t-1)}$ and $P_N^{(t)}$ in $B_N^{(t)}$;
  Determine the global best solution from $B_N^{(t)}$;
  if migration condition gets satisfy **then**
    Perform local or global migration;
  end if
end while

${\alpha_p}^2$ and ${\beta_p}^2$ determine the probability of a q-bit to be in state “0” and state “1” respectively with the following constraint [Eq. (4)].

$$\alpha_p^2 + \beta_p^2 = 1; 0 \leq \alpha_p \leq 1, 0 \leq \beta_p \leq 1 \tag{4}$$

As quantum bit (Q) with single q-bit (q_p) i.e., $p = 1$, can depict two states (“0” and “1”), a quantum bit (Q) with two q-bits (q_p) i.e., $p = \{1, 2\}$, symbolized as Eq. (5), can illustrate the linear superposition of four states (“00”, “01”, “10” and “11”) simultaneously according to Eq. (6).

$$Q = \left\langle \begin{array}{c} \alpha_1|\alpha_2 \\ \beta_1|\beta_2 \end{array} \right\rangle \tag{5}$$

$$Q = (\alpha_1 \times \alpha_2)\langle 00\rangle + (\alpha_1 \times \beta_2)\langle 01\rangle + (\alpha_2 \times \beta_1)\langle 10\rangle + (\beta_1 \times \beta_2)\langle 11\rangle \tag{6}$$

For instance, Eq. (7) presents a quantum bit (Q) with two q-bits where α and β are initialized with a value according to the range defined in Eq. (4).

$$Q = \left\langle \begin{array}{c} 1/\sqrt{2}|1/\sqrt{2} \\ 1/\sqrt{2}|1/\sqrt{2} \end{array} \right\rangle \tag{7}$$

Therefore, the linear suposition of four states in quantum bit (Q) is illustrated according to Eq. (8).

$$Q = (1/\sqrt{2} \times 1/\sqrt{2})\langle 00\rangle + (1/\sqrt{2} \times 1/\sqrt{2})\langle 01\rangle + (1/\sqrt{2} \times 1/\sqrt{2})\langle 10\rangle + (1/\sqrt{2} \times 1/\sqrt{2})\langle 11\rangle \tag{8}$$

Likewise, a quantum bit (Q) with m q-bits can represent 2^m states simultaneously. This concept of quantum computing advantages the QIEA over other meta-heuristic algorithms in terms of better population diversity, enhanced exploration and exploitation trade-off, less number of individuals required to explore the large search space, and attains the global optimal solution in less time comparatively [28]. Moreover, QIEA observes the quantum bits to classical individuals. The complete flow of the QIEA is illustrated in Algorithm 1.

In QIEA, a population of N quantum bits ($Q = \{Q_1, Q_2, \cdots, Q_i, \cdots, Q_N\}$) is initialized where Q_i consists of m q-bits where, each q-bit is defined as $[\alpha\ \beta]^T$. In the (t^{th}) iteration, the generated quantum bits ($Q_N^{(t)}$) are used to obtain equal number of binary representations ($P_N^{(t)}$) according to the observation process whose pseudo-code is depicted in Algorithm 2. Further, each representation in the $P_N^{(t)}$ is evaluated for the fitness. The calculated fitness are then used to determine the best solutions and stored in $B_N^{(t)}$. The solution with the best fitness among $B_N^{(t)}$ defines the global best solution in the (t^{th}) iteration. Thereafter, each q-bit (q_p) in quantum bits ($Q_N^{(t)}$) are updated through the rotational quantum gates which is formulated as Eq. (9) [36].

TABLE I
LOOKUP TABLE FOR $\triangle\theta_i$

x_i	b_i	$f(x) \geq f(b)$	$\triangle\theta_i$
0	0	F	θ_1
0	0	T	θ_2
0	1	F	θ_3
0	1	T	θ_4
1	0	F	θ_5
1	0	T	θ_6
1	1	F	θ_7
1	1	T	θ_8

F: False; T: True

$$\alpha_p^{(t)} = [cos(\triangle\theta) * (\alpha_p^{(t-1)}) - (sin(\triangle\theta) * \beta_p^{(t-1)})] \tag{9}$$

where, $\beta_i = \sqrt{1-(\alpha_i^{(t-1)})^2}$ and $\triangle\theta$ represent an angle which determines the angular approximation of each q-bit and controls its rotation value. The value of $\triangle\theta$ is identified according to the Table I. Lastly, the migration process is performed to update the $B_N^{(t)}$ once the migration condition is satisfied. Here, the migration condition is a designing parameter and can induce variations in the quantum bits. In QIEA, there are two types of migrations, namely local migration and global migration. In local migration, some of the solutions in $B_N^{(t)}$ are replaced with the best solution among them whereas in global migration, the global best solution in the t^{th} iteration replaces every solution in $B_N^{(t)}$.

III. Proposed Feature Selection Method

This paper presents an improved quantum-inspired evolutionary-based feature selection (IQIEA-FS) method for the classification of fake-face images. Fig. 2 illustrates the block diagram of the proposed method while the pseudo-code of the same method is detailed in Algorithm 3. There are three

Algorithm 2 Observation Process

Input: For a quantum bit (Q_i) defined as $\{q_1|q_2|\cdots|q_p|\cdots|q_m\}$ where $q_p = [\alpha_p\ \beta_p]^T$;.
Output: $X_i = \{x_1, x_2, \cdots, x_p, \cdots, x_m\}$: Binary representation of Q_i.

while p≤ m **do**
  if random [0,1) $\leq |\alpha_p|^2$ **then**
    $x_p = 1$;
  else
    $x_p = 0$;
  end if
end while

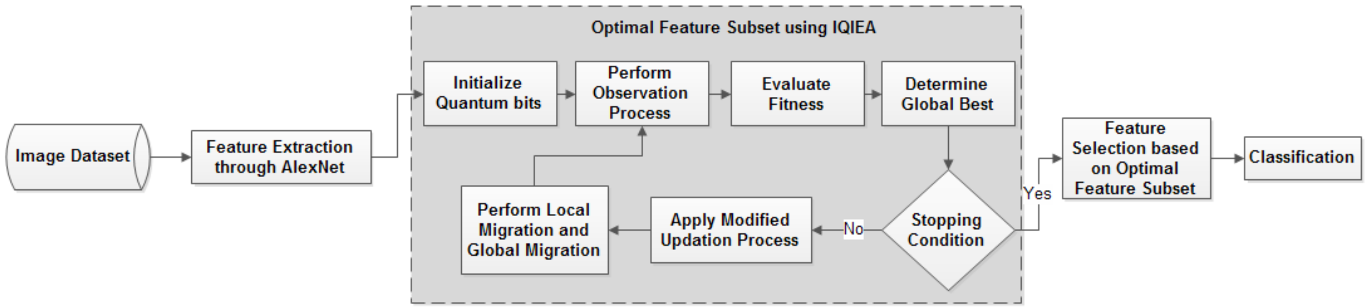

Fig. 2. Block diagram of the proposed IQIEA-FS method for image classification.

Algorithm 3 Proposed Feature Selection Method (IQIEA-FS) for Image Classification

Input: Let X be the colored image dataset and I be the test image. Assume mutation rate (μ_r) and initial value of α_p according to the range defined in Eq. (4).
Output: Class label for T.

Perform feature extraction for X and I using the AlexNet;
Initialize N quantum bits, $\{Q_1, Q_2, \cdots, Q_i, \cdots, Q_N\}$, of IQIEA. Each Q_i consists of m q-bits, $\{q_1|q_2|\cdots|q_p|\cdots|q_m\}$, where each q_p is is $[\alpha_p \;\; \beta_p]^T$ and is initialized with assumed value of α_p as $\beta_p = \sqrt{1-(\alpha_p)^2}$;
while termination condition does not meet **do**
  Represent each Q_i into binary form according to the observation process defined in Algorithm 2;
  Generate the feature subset from the extracted features for each Q_i by selecting only those features which correspond to the active value (i.e., 1) in the binary representation;
  Compute the fitness in terms of 10-fold cross validation accuracy for each feature subset;
  Determine the best feature subset;
  Update each Q_i according to IQIEA;
end while
Optimal feature subset is considered to train the considered classifier and determine the label for I.

phases in the proposed method, namely feature extraction, optimal feature selection, and classification. In first phase, the considered fake-face image dataset is processed through a pre-trained AlexNet to extract features. For this, the output of the last fully connected layer of AlexNet i.e., F_8, is considered which returns 1000 features for an image. As the possible number of feature subsets is approx. $1.072e+301$ (i.e., 2^{1000}), the optimal feature subset is obtained. To do so, the second phase employs a new quantum-inspired evolutionary algorithm, termed as improved quantum-inspired evolutionary algorithm (IQIEA). In IQIEA, the number of q-bits (q_m) considered in a quantum bit (Q) is equivalent to the number of extracted features for an image. In the considered scenario, the set of N quantum bits is represented as Eq. (10).

$$Q = \{Q_1, Q_2, \cdots, Q_i, \cdots, Q_N\} \tag{10}$$

where, $i = \{1, 2, \cdots, N\}$ and i^{th} quantum bit (Q_i) is formulated as Eq. (11).

$$Q_i = \{q_1|q_2|\cdots|q_p|\cdots|q_m\} \tag{11}$$

where, $p = \{1, 2, \cdots, m\}$ and $m = 1000$. Each q-bit (q_p), defined as $[\alpha_p \;\; \beta_p]^T$, initializes both states ($|0\rangle$ and $|1\rangle$) with an equal probability amplitude i.e., $1/\sqrt{2}$. Further, IQIEA generates a binary representation for each Q_i according to the observation process. To do the same, the proposed method considers only those features which have an active value (i.e., 1) in the binary representation of corresponding Q_i. Lastly, the third phase employ kNN with 10-fold cross validation as a classifier to measure the fitness in terms of accuracy. Thereafter, each quantum bit is updated according the proposed IQIEA.

A. *Improved Quantum-Inspired Evolutionary Algorithm (IQIEA)*

An equilibrium between exploration and exploitation is the essence of a meta-heuristic algorithm which assists in evading local optima and attains better solution precision. In QIEA, this trade-off is controlled through Eq. (9) which formulates the rotational quantum-gate [36]. However, there is no mutation operation in later iterations of QIEA which may entrap QIEA into local optima. Therefore, in the proposed IQIEA, the rotational quantum-gate is integrated with a mutation operation to enhance the exploration ability. Algorithm 4 details the pseudo-code of the modified updation process. Moreover, the local migration process of the IQIEA algorithm is modified by replacing some of the solutions in $B_N^{(t)}$ with the global best solution which advantages the IQIEA algorithm in achieving better solution precision.

Algorithm 4 Modified Updation Process

For each quantum bit (Q_i) defined as $\{q_1|q_2|\cdots|q_p|\cdots|q_m\}$ where $q_p = [\alpha_p \;\beta_p]^T$;
while i$\leq$ m **do**
  Determine the $\triangle\theta$ from the loop table [Table I];
  if rand $\geq \mu_r$ **then**
    $\alpha_i^{(t)} = [cos(\triangle\theta) * (\alpha_i^{(t-1)}) - (sin(\triangle\theta) * \beta_i^{(t-1)})]$ where, $\beta_i = \sqrt{1-(\alpha_i^{(t-1)})^2}$;
  else
    $\alpha_i^{(t)} = rand$;
  end if
  Update $q_i^{(t)} = \alpha_i^{(t)}$;
end while

TABLE II
PARAMETER SETTINGS.

Parameters	QIEA-FS	IQIEA-FS
Number of Quantum bits	10	10
Number of q-bits	1000	1000
Maximum iterations	100	100
mutation rate (μ_r)	–	0.3

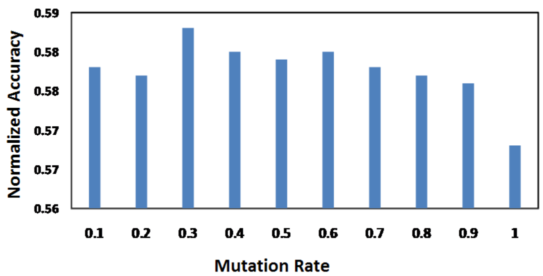

Fig. 3. Determination of Mutration rate (μ_r).

IV. Experimental Results

All experiments are simulated on MATLAB 2017a in a computer with Intel Core i7-7500U having 8GB RAM and GeForce 940MX GPU. The performance of the proposed IQIEA based feature selection (IQIEA-FS) method is studied against AlexNet-kNN and QIEA based feature selection (QIEA-FS), in terms of two performance parameters, namely number of selected features and classification accuracy. Table II lists the parameter settings of the considered methods. The number of quantum bits and maximum iterations is considered as 10 and 100. To minimize the interference, 30 runs of each method is executed to report the results. Moreover, the mutation rate (μ_r) in the mutation operation is set to 0.3 as IQIEA-FS achieved the highest normalized accuracy on this value when studied empirically. Fig. 3 represents the same in the form of a histogram over different values of μ_r. The different values of θ are considered as follows; ($\{\theta_1$, θ_2, θ_4, θ_6, θ_7, $\theta_8\} = 0$), ($\theta_3 = 0.03\pi$), and ($\theta_5 = -0.03\pi$) [36]. Moreover, the local migration condition and global migration condition for both QIEA and IQIEA are 1 and 10 respectively.

A. Considered Dataset

For experimental analyses, a publicly available manually created fake-face dataset, namely Real and Fake Face Detection by Yonsei University [34], is considered. This fake-face dataset is a small dataset that consists of finely labeled color images for two classes, namely real and fake. Figure 5 illustrates some sample images for both classes. Further, this dataset consists of 1081 real-face images and there are 906 manually created fake-face images. To maintain unbiasedness, the number of images considered from each class is the minimum number of images among both the classes i.e., 906. Moreover, the size of each image is 600 $\times$ 600 which is reshaped to 227 $\times$ 227 to fit the AlexNet input layer.

(a) Real: Image1 (b) Real: Image2 (c) Real: Image3

(d) Fake: Image1 (e) Fake: Image2 (f) Fake: Image3

Fig. 4. Sample images corresponding to each class, taken from the Real and Fake Face Detection dataset [34].

B. Performance Analysis

Table III tabulates the performance of the considered methods namely, AlexNetkNN, QIEA-FS, and IQIEA-FS, in terms of normalized accuracy and number of features selected. From the table, it can be observed that the proposed IQIEA-FS method returns the minimum average number of selected features i.e., 333.30, while QIEA-FS gives 666.60 average number of selected features. This shows that the proposed method eliminates 50% features from the feature set as compared to the QIEA-FS method. Further, the relevance of the selected features can be analyzed through the accuracy which is 58.3% for the proposed IQIEA-FS method. This is the best among the AlexNet-kNN and QIEA-FS methods. Also, it can be observed from Table III that IQIEA-FS attains an increase of 3% accuracy in comparison to the AlexNet-kNN method. However, the accuracy of the QIEA-FS method is competitive but with more number of selected features. Thus, from the results of Table III, it can be validated that the IQIEA-FS method returns the best accuracy with the minimum number of features. Moreover, Fig. 5 illustrates the variation in accuracy attained by the considered methods over 30 runs. From the figure, it can be observed that QIEA-FS method reports the minimum variation in accuracy while IQIEA-FS method has comparatively lower variation than AlexNet-kNN method. Further, the convergence behavior in Fig. 6 validates that IQIEA-FS is better than QIEA-FS in attaining the accuracy over the number of iterations. It can be examined that the accuracy reported by the proposed IQIEA-FS method is achieved in less than 12% of the iterations as compared to the number of iterations taken by the QIEA-FS method.

To verify the robustness of the proposed method, the number of selected features over 30 runs are analyzed. Fig. 7 depicts the same through Boxplot. Similar information is also available in Table III. The number of selected features are reported as minimum count, maximum count, and average count. As the AlexNet-kNN method is not performing feature selection,

TABLE III
CLASSIFICATION RESULTS ON CONSIDERED DATASET OVER 30 RUNS.

	AlexNet-kNN	QIEA-FS	IQIEA-FS
Mean Normalized Accuracy	0.558	0.579	**0.583**
Minimum Number of Selected Features	1000	508	**319**
Maximum Number of Selected Features	1000	935	**347**
Average Number of Selected Features	1000	666.60	**333.30**

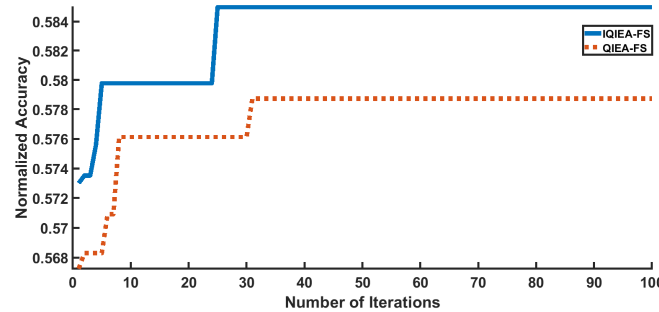

Fig. 6. Convergence trends of IQIEA-FS and QIEA-FS methods in terms of Normalized Accuracy.

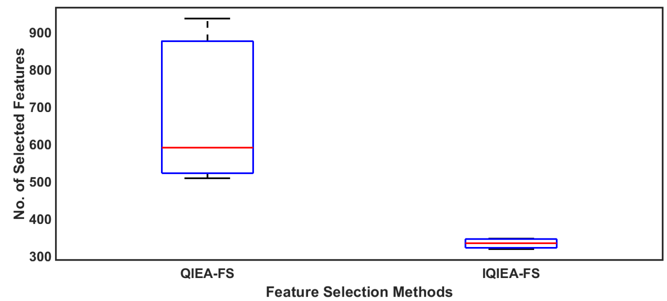

Fig. 7. Boxplot for the number of selected features by considered methods over 30 runs.

the number of selected features are 1000 in all the counts. However, the feature counts of the proposed IQIEA-FS method are 319, 347, and 333.30 which are smaller than the feature counts for the QIEA-FS method respectively. Therefore, it can be concluded that the IQIEA-FS method is more consistent than the QIEA-FS method.

Therefore, it is pertinent to state that the proposed IQIEA-FS method selects prominent features by rejecting irrelevant features and attains higher classification accuracy with better solution precision.

V. CONCLUSION

This paper presents a new feature selection method, improved quantum-inspired evolutionary-based feature selection, for the classification of manually created fake-face images. The proposed method initially extracts features of an image through AlexNet, a pre-trained deep learning model. The extracted features are processed through the proposed improved quantum-inspired evolutionary algorithm to select an optimal feature subset. Finally, the classification is performed with the elicited feature subset through the kNN classifier with 10-fold cross-validation. The computational complexity of the proposed algorithm is O($M \times N \times m$) [37], where M, N, and m corresponds to the maximum iterations, number of quantum bits, and number of q-bits, respectively. The experimental evaluations are conducted on a publicly available manually created fake-face image dataset, namely Real and Fake Face Detection by Yonsei University and compared with two methods, namely AlexNet-kNN and quantum-inspired evolutionary algorithm based feature selection. The evaluation parameters considered for comparison are classification accuracy and the number of selected features. The performance comparison clearly exhibits that the proposed method is efficient than the other considered methods in terms of reducing the insignificant and redundant features and attains high classification accuracy. The future work includes the enhancement of the proposed method by fine-tuning its parameters and incorporating the pre-processing phase such as noise-filtering. Additionally, different classifiers can be investigated for better accuracy. Finally, the performance of the proposed method may be evaluated on other classification datasets.

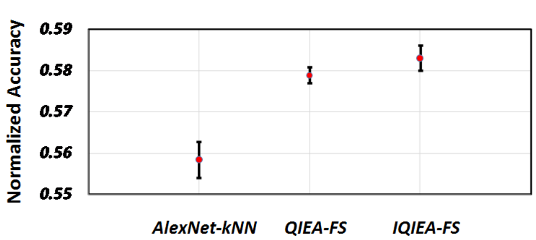

Fig. 5. Variation analysis of Normalized Accuracy in 30 runs.

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