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# Robust features extraction from shape signature for fish images classification

**Ali Ahmed[1], Sherif Hussein[2], Younis Ibrahim Gali[3]**
[1]Department of Information Technology, College of Computers and Information, Menofia University, Sheben Elkom, Egypt
[2]Department of Computer Engineering, Faculty of Engineering, Mansoura University, Mansoura, Egypt
[3]Department of Computer Scince, College of Engineering and Computer Science, Mustaqbal University, Buraydah, Saudi Arabia

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**ABSTRACT**

Recently, the process of fish species classification has become one of the most challenging problems addressed by researchers. In this work, a robust scheme to classify fish images based on robust feature extraction from shape signatures is proposed. First, the image contour is fitted using one of the common approaches named radial basis function neural network (RBFNN) fitting to obtain image centroid. Afterward, prominent features from the shape signature are extracted. These features are representative of fish shapes because they can distinguish the characteristics of each class as well as being relatively robust to scale and rotation changes. Finally, for the classification process purpose, RBFNN is used again for image classification against one of the most commonly used classification techniques called support vector machine (SVM). The proposed paradigm has been applied to a standard fish dataset acquired from a live video dataset grouped into twenty-three clusters representing specific fish species. The resulting accuracy based on SVM and RBFNN was 90.41% and 98.04%, respectively.



***Corresponding Author:***

Ali Ahmed
Department of Information Technology, College of Computers and Information, Menofia University
Sheben Elkom, Egypt
Email: ali.ahmed@ci.menofia.edu.eg

## 1. INTRODUCTION

Fish species classification is a significant task for researchers of biology and marine ecology to regularly approximate the abundant of fish species in their natural habitats and to track their population changes. Many state-of-the-art studies concerning fish segmentation and classification have been done using different methods and systems. Jalal *et al*. [1] proposed a hybrid approach for fish detection and classification based on optical flow and Gaussian mixture models with YOLO deep neural network and they obtained an accuracy rate of 91.6%. Other researchers Almero *et al*. [2] used tree and artificial neural networks (ANN) for underwater fish image detection and classification and they achieved an accuracy rate of 93.6%. Convolutional neural network (CNN) is a recent approach used by many researchers for fish image classification [3]-[5] and they obtained an accuracy rate of 98.1%, 87.74%, and 96.8% consequently.

Iqbal *et al*. [6] proposed a deep learning approach for identification and classification of fish species using AlexNet model and achieved 90.48% accuracy rate. Cui *et al*. [7] proposed a CNN for fish image detection and obtained an accuracy rate of 97.5%. Others proposed deep learning method designed to differentiate the classification of fish in aquatic fish farms and they achieved both an accuracy rate 96% and a recognition rate of 98% [8]. Montalbo and Hernandez [9] developed VGG16 deep convolutional neural network (DCNN) to classify Verde Island fish species and they achieved an accuracy rate of 99%. They generated augmented synthetic data for training and testing the VGG16 model and the augmented images were flipped, rotated, cropped, zoomed, and sheared to obtain robust number of features for classification. The study implemented in [10] proposed a transfer learning-based (ResNet50 network) for classifying fish species using underwater images and was achived 98.4% accuracy rate. Ahmed *et al.* [11] used machine learning-based classification model support vector machine (SVM) for fish infection and they obtained an accyracy rate of 94.12%. Inception-V3 deep learning algorithm for fish image classification is proposed in [12]. To overcome the problems due to low-quality images and small data, they used data augmentation improve the prediction accuracy.

Deep learning neural network (DNN) for automatic classification of fish species is proposed in [13]. In this work, a novel training regime is developed to cue the scarcity of training data and achieved a classification rate of 94%. Andayani *et al.* [14] used a combination of geometric invariant moment, gray-Level co-occurrence matrix (GLCM), and hue saturation value (HSV) feature extraction methods to extract fish images features and for fish species classification purposes, they used probabilistic neural network (PNN) method utilized to properly classify fish species and achieved 89.65% accuracy rate. Others utilize convolutional neural networks (CNN) using deep learning for fish classification [15]-[17]. Sun *et al.* [18] proposed DNN and super-resolution approach methods for explicitly learn the discriminative features from low-resolution images. Few-shot deep learning architecture was used for automatic classification of underwater fish species with limited data [19]. Sengar *et al*. [20] provide a non-destructive computer-aided method for the identification of quality differences between pesticides exposed and freshwater fish. Christensen *et al.* [21] purposed a deep convolutional neural network called optical fish detection network (OFDNet) for fish image detection and is focused on applications in the poorly conditioned North and Baltic Sea and is initially developed for the purpose of recognizing herring and mackerel. SVM technique for improved classification of fish species using the shape features of fish image is proposed in [22]. A recent survey on fish classification (FC) techniques is introduced to help researchers follow up the future research directions [23]. Some recent research summary in fish classification is presented in Table 1.

Table 1. Summarization of some published fish image classification studies

| Ref. | Year | Fish features | Classifier | Classification rate |
|---|---|---|---|---|
| Jalal *et al*. [1] | 2020 | Shape and texture features | GMM, optical flow algorithms and deep neural network. | 91.6% |
| Almero *et al*. [2] | 2020 | Color features | Classification tree and artificial neural network | 93.6% |
| Liang *et al*. [3] | 2020 | Shape features | Convolutional neural network | 98.1% |
| Knausgård *et al*. [4] | 2022 | Generic features | Convolutional neural network | 87.74% |
| Böer *et al*. [5] | 2021 | Morphological features | DeepLabV3 and PSPNet models | 96.8% |
| Iqbal *et al*. [6] | 2019 | Generic features | AlexNet model | 90.48% |
| Cui *et al*. [7] | 2020 | Generic features | Convolutional neural network | 97.5% |
| Zhang *et al*. [8] | 2021 | Morphological features | Convolutional neural network | 96% |
| Montalbo and Hernandez [9] | 2019 | Generic features | VGG16 DCNN Model | 99% |
| Mathur and Goel [10] | 2021 | Generic features | ResNet-50 Model | 98.44% |
| Ahmed *et al*. [11] | 2022 | Statistical & color features | SVM classifier | 94.12% |
| Lan *et al*. [12] | 2020 | Shape and texture features | Deep CNN | 89% |
| Allken *et al*. [13] | 2018 | Shape features | A deep learning neural network | 94% |
| Andayani *et al.* [14] | 2019 | Co-occurrence Matrix and Geometric invariant moment | Probabilistic neural network | 89.65% |
| Khalifa *et al*. [15] | 2019 | Color features | Convolutional neural networks | 85.59% |
| Deep and Dash [16] | 2019 | Color features | Convolutional neural networks | 96.29% |
| Ma *et al*. [17] | 2018 | Color features | Transfer learning & CNN | 97.19% |

In this paper, RBFNN and SVM techniques for fish image classification were presented and evaluated against the fish shape features. The contribution of this work can be summarized as:
- Extracted robust features for fish image classification. These features are not only good to represent fish shape signatures because they can distinguish the characteristics of each class but also are relatively robust to the scale and rotation change.
- RBFNN is used twice in this work. First, it is used for fitting image contour, and second, it is used for image classification.
- Providing comparative analytics of the proposed system with one of the well-known methods named SVM.

The structure of this study is organized into the following sections: Section 2 handles in detail the proposed fish features extraction, as well as the classification techniques used; Section 3 discusses in detail the experimental results of the proposed approach, and finally, the contribution of the proposed work as well as the suggestion for future research are concluded in section 4.

## 2. METHOD

The proposed fish classification approach in this study is shown in Figure 1. In our study, the proposed system was decomposed into two stages: the feature extraction stage and the classification stage. In the following subsections, the feature extraction stage, as well as the classification stage are explained in detail with some experimental results.

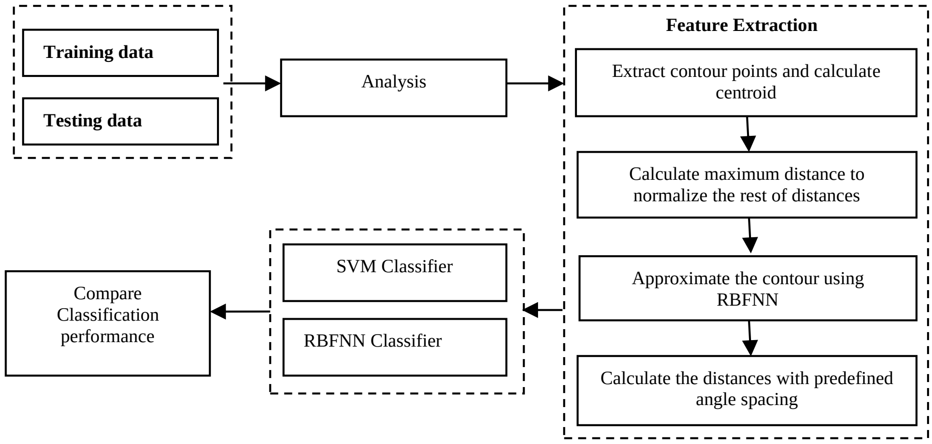


Figure 1. The proposed approach for fish image classification

### 2.1. Features extraction from shape signature

At this level, contour descriptors are represented by shape signatures that are computed from the contour points of the geometry. Centroid contour distance (CCD) is one of the commonly used shape signature approaches [24], [25]. There are many characteristics of CCD curve sequence such as its translation-invariant, rotation-invariant, and scale-invariant under certain normalizations. CCD series displays the distances between the contour boundary points in each picture and the centroid of the contour. The picture border is used to extract feature points, which are then stored in an ordered data-structure. The description of shape sequences is used to extract this vital information from the picture border. CCDs formulation will be discussed in the remaining of this section. In the next section, the curve fitting using RBFNN will also be discussed in detail. The image shape centroid is calculated using (1) and (2).

$$x_{cen} = \frac{1}{N}\sum_{i=1}^{N} x(i) \text{ and} \tag{1}$$

$$y_{cen} = \frac{1}{N}\sum_{i=1}^{N} y(i), \text{where } i = 1,2,\dots,N \tag{2}$$

The number of boundary points $N$ and the coordinate set of boundary points are represented by pairs $\left(x(i), y(i)\right)$. The centroid contour distance (CCD) sequence can be computed using (3).

$$D_i = \sqrt{(x(i) - x_{Cen})^2 + (y(i) - y_{Cen})^2} \tag{3}$$

To obtain scale-invariant features, these distances features are normalized by the maximum CCD and consequently stored in an ordered data structure. An example of some fish images and their maximum CCD with contour points is shown in Figure 2.

### 2.2. RBFNN for image contour fitting

RBFNN is applied in many study areas such as regression, classification, and curve fitting [26]-[28]. RBFNN architecture consists of three layers. The first layer serves as an input vector for each unit in the subsequent hidden layer. The hidden layer is activating each unit using RBF. Then, the output layer is a linear combination of the activations using all hidden layers. It is mainly depending on the associated weights combined with the links between both the previous layer (hidden layer) and the current layer (output layer). RBFNNs can be learned using one of the learning strategies. In this study, the parameters of RBFNN were adapted to find the regression function between the CCD angle and the corresponding distance. RBFNN parameters include the number of hidden layer units, radial basis function centers, and standard deviations to minimize the root mean square errors under 1% between the testing data.

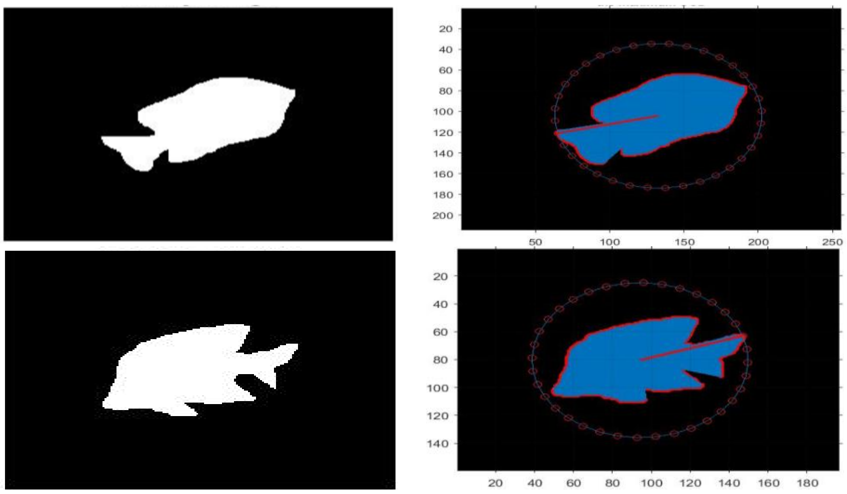


Figure 2. Two binary images and their corresponding contours and the maximum CCDs

## 3. CLASSIFICATION

The fish dataset was further classified according to the extracted features (36 features) using two well-known classification methods, namely RBFNN and SVM. The two classification techniques are compared with recent classification techniques' performance found in the literature that identifies the different fish species. These classification methods will be discussed in the following sub-sections.

### 3.1. RBFNN for fish images classification

The first classification method that was applied to the fish dataset was chosen to be RBFNN. Contrary to its use in the feature extraction stage, RBFNN is used here for fish image classification according to the normalized features obtained from the feature extraction stage. By allocating the input vector to the class with the highest score, the classification decision is made. For each fish picture, the contour points were used to calculate the image centroid. The largest distance was then used to standardize the distances between these spots and the centroid. The normalised distances acquired are regarded as a dependent variable. As the independent variable, the angles of these normalized distances were determined relative to the max CCD to the image centroid. Finally, RBFNN was used to precisely determine the optimum curve for each fish in the dataset that minimises the mean square error.

### 3.2. Support vector machine classification

The second classification technique used in this study is SVM. It is considered one of the common ML techniques used for solving both regression and classification problems. SVM was first appeared in [29] and has been effectively used in many research areas [30]-[32]. The SVM classifier is primarily used to categorize unknown dataset samples by constructing a classification model from training data. SVM performance is primarily affected by two classification parameters known as penalty and kernel parameters. During the training phase, the penalty parameter plays an important role as a tradeoff between data error reduction and margin maximization. The kernel parameter is also crucial in determining the nonlinear mapping between the image input data and the multi-dimensional feature space.

## 4. RESULTS AND DISCUSSION

### 4.1. Dataset

In this study, the performance of the proposed system is tested against a well-known fish dataset acquired from a live video [33]. This dataset contains approximately 27,370 fish images divided into twenty-three different categories. Each category is presented by a specific species. The system platform used in the experiments is implemented based on Intel(R) core (TM) i7-4460 CPU, 3.20 GHz, 10 GB RAM, and Matlab tools (R2021a). To choose the number of feature points, we select them according to the angles. These feature points are dispersed evenly beginning at an angle of $0^{o}$ relative to the greatest distance between the contour and the centroid. In this study, we choose angles $10^{o}$, $20^{o}$, and $30^{o}$ to obtain 12, 18, and 36 feature points respectively. Then, the dataset is distributed as 80% of the features were then fed to the RBFNN for training and 20% for testing.

### 4.2. Feature extraction results

In this section, some results of the feature extraction process are shown to prove the robustness of the feature extraction technique. Figure 3 shows two feature plots for two given binary images from fish species when 36 features are selected. It has been shown from the figure that the feature plots for two images from different fish species are different. On the other hand, the feature plots for images from the same species have similar curves and that proved the robustness of the proposed feature extraction method. The graphical representations of CCD results for four different fish classes with an angle θ=20° are shown in Figure 4. These graphs show the distances between the image centroid and the contour points starting from a point located at the maximum distance of the fish image. The average value of CCD features for each class is shown in Figure 5. It has been clear from the figure that the four fish shape classes have different graph representations, proving that CCD features can distinguish fish shapes well.

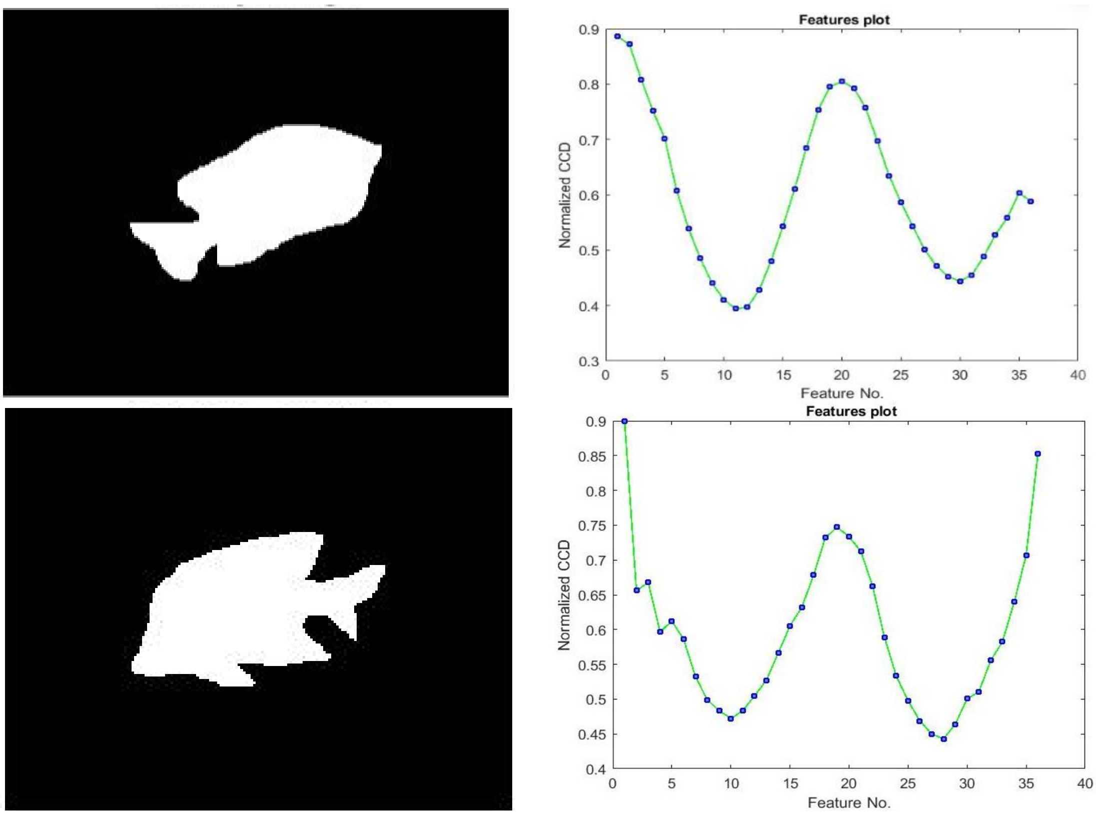


Figure 3. Two binary images and their corresponding feature plots when 36 features are selected

### 4.3. Fish images classification results

SVM classifier is tested against the selected fish dataset using the Gaussian kernel. The main challenge of SVM is the overfitting classification. So, the optimization of the two parameters of SVM plays an important role to improve the accuracy rate. While increasing the parameter $\sigma$, that results increase the fitting for the training data at the price of the generalization error, it might result in an overfitting issue. Furthermore, the other SVM parameter C achieves a balance between smoothing decision boundary and prefectly categorizing the training points. As a result, optimizing these parameters will be a top focus to attain a higher categorization rate. Using a Bayesian optimization strategy, the SVM parameters were adjusted by lowering the misclassification rate on the datasets and, as a result, assuring a high classification rate for the provided dataset. The findings of the first classifier, SVM, in this study are superior to the results of the second classifier, RBFNN. The excessive number of parameters employed by RBFNN, on the other hand, might be reflected in the algorithm complexity and, as a result, lead to worse performance if the selected parameters are not sufficiently tuned.

Table 2 shows the performance indices comparison of the two proposed classifiers. The processing times of SVM and RBFNN classifiers were assessed and separated into distinct task periods consumed during the training and validation stages. This table clearly shows that the RBFNN classifier takes longer than SVM to achieve the objective function value in terms of time used and classification accuracy. SVM classifier, on the other hand, used the least amount of time while maintaining a reasonably high classification accuracy rate.

Table 3 shows a comparison between the performance of RBFNN and SVM classifiers. It is clear from the table that the classifiers gave various accuracies according to various interval angles. SVM classifier gives a higher accuracy rate at different interval angles (different numbers of features selected) and the number of iterations than those obtained by RBFNN classifier. SVM achieves the best classification accuracy of 98.04% at interval angle=20$^{\circ}$(i.e. the number of features equals 18) and a low accuracy rate at angle=10$^{\circ}$(i.e. the number of features equals 18).

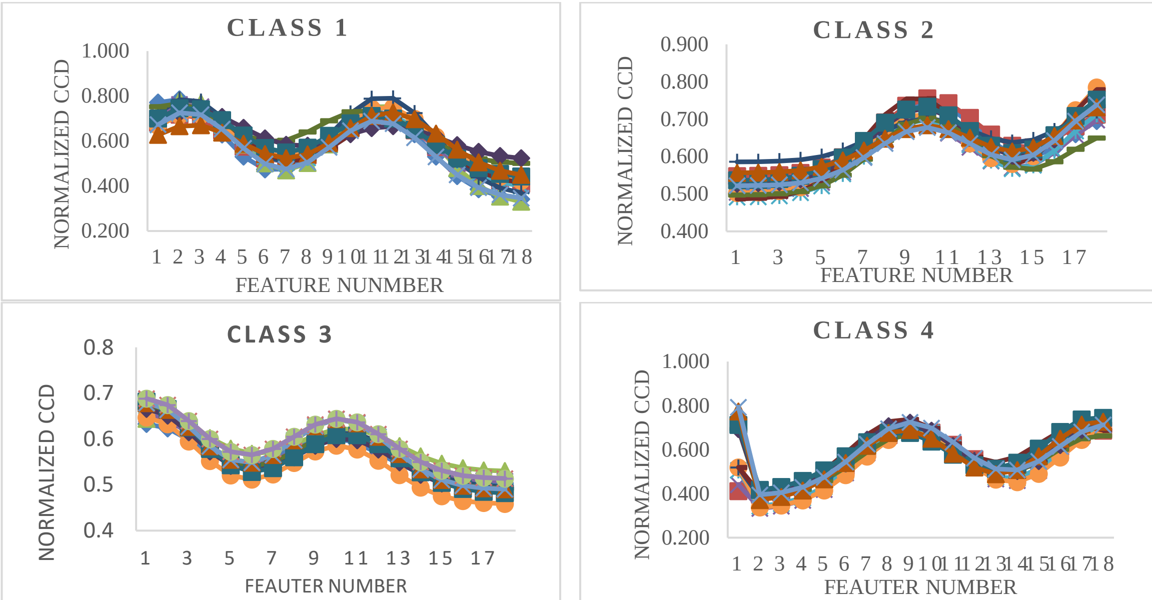


Figure 4. Feature graphs for four different classes when 18 features are selected

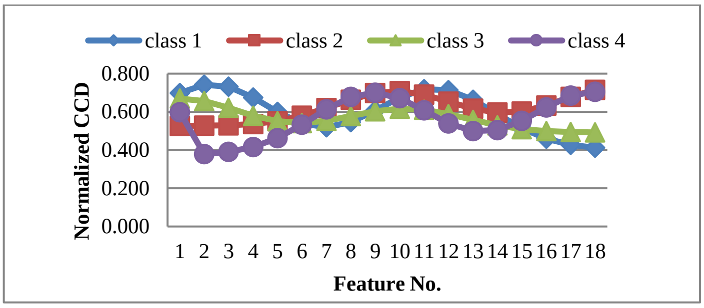


Figure 5. Average feature graphs for the four classes mentioned in Figure 4

Table 2. Performance indices of the two classifiers

| Factor | RBFNN classifier | SVM classifier |
|---|---|---|
| Total Spent Time (s) | 167.36 | 30.306 |
| Total Evaluation Time (s) | 114.27 | 31.011 |
| Function Evaluation Time (s) | 0.379 | 0.124 |
| Objective Function Value | 0.02404 | 0.026206 |

Table 3. Performance accuracies of the proposed system at different number of features

| Method | Performance accuracies at different number of features | | |
|---|---|---|---|
| | At 36 features | At 18 features | At 12 features |
| SVM | 94.12% | 98.04% | 96.15% |
| RBFNN | 89.01% | 90.41% | 89.95% |

## 5. CONCLUSION

RBFNN has been proven to outperform other methods when used in complex applications related to regression and classification. In this study, RBFNN has been applied twice in two-step feature extraction and classification stages. The first stage is used for finding the best-fitting curve of a fish image from its contour data points. This step is significant for extracting robust features for image contour. The obtained features are not only good to represent fish shape signatures because they can distinguish the characteristics of each class but also are relatively robust to the scale and rotation change. Second, RBFNN was utilized again in the classification stage for comparison purposes as one of the commonly used classifiers. With all the number of features selected, the performance of the SVM is superior to the RBFNN classifier. The parameters of the RBF kernel used in the SVM classifier play an important role in further SVM accuracy enhancement. Therefore, several parameter values were investigated to achieve the best results. In addition, a time complexity analysis was performed to measure the time required to find the classifiers' parameters. Moreover, the proposed system is recommended for the investigation of other pattern classification problems that rely on complex-shape image features to achieve superior accuracy.

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## BIOGRAPHIES OF AUTHORS

**Ali Ahmed** is an Associate professor of information technology with the Menofia University, faculty of computers and information. He holds a B.Sc. in pure mathematics and computer science from the faculty of science at Menoufia University, an M.Sc. in computer science from the faculty of science at Suez Canal University, and a Ph.D. in computer science from college of Engineering, Tokushima University, Japan in 2011. He is currently an associate professor at information technology department, faculty of computers and information, Menofia university, Egypt. His research interests include computer vision, target motion analysis, and image processing, Arabic OCR systems. He is an author of many image processing and machine learning publications and a reviewer for many scholar journals. He can be contacted at email: ali.ahmed@ci.menofia.edu.eg.

**Sherif Hussein** received the B.S. and M.S. degrees (Hons.) in computer engineering from Mansoura University, Egypt, the Ph.D. degree from the University of Strathclyde, Glasgow, U.K., in 2003, and the M.B.A. degree (Hons.) from Cardiff Metropolitan University, Cardiff, U.K. He was a Postdoctoral Researcher at VNIIM, Saint Petersburg, Russia. He is currently a Professor with the Department of Computer Engineering and Control Systems, Mansoura University; a Computer Technical Consultant for the Ministry of Higher Education, Egypt; and an author of about 40 publications. His research interests include cloud computing, data science, image and signal processing, modeling, and artificial intelligence. He is a member of ICMI and the Institute of Engineering and Technology (IET). He received the ORS Award, the International Scholarship Award, and the University of Strathclyde Award. He can be contacted at email: sherif_hussein@mans.edu.eg.

**Younis Ibrahim Gali** is an Assistant professor with double track the major track computer science and other is statistics. He holds BSc (University of science and Technology), MSc (Gezira University) and Ph.D. (National Ribat University) in computer science. In addition, he a ward Ph.D. in statistics (Omdurman Islamic University). He currently an Assistant professor, computer science department, college of Engineering and computer science, Mustaqbal University, Saudi Arabia. His research interest's area includes Artificial intelligence (ML and DL), forecasting using ANN and statistics models and bioinformatics (DNA and RNA). He can be contacted at email: yigali-t@uom.edu.sa.