Journal of King Saud University – Computer and Information Sciences xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of King Saud University – Computer and Information Sciences

journal homepage: www.sciencedirect.com

A survey on fish classification techniques

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ARTICLE INFO

Article history:
Received 4 April 2020
Revised 12 July 2020
Accepted 13 July 2020
Available online xxxx

Keywords:
Features extraction
Shape features
Texture features
Color features
Image segmentation
Fish classification algorithms

ABSTRACT

Fish classification (FC) is an expansively studied problem in the domains of image segmentation, pattern recognition, and information retrieval. It has been applied in a countless number of domains including target marketing. Meanwhile, governments are obliged to maintain the fish supply and balance between the ecosystem, commercial, agriculture field, marine scientists, and industrial arena of fish including the nutrition and canning factories. The various FC techniques performance is compared relying on the availability of preprocessing and feature extraction methods, the number of extracted features and classification accuracy, the number of fish families/species recognized. This survey also reviewed the use of Databases such as Fish4-Knowledge (F4K), knowledge database, and Global Information System (GIS) on Fishes and other FC databases. The study on preprocessing methods features extraction techniques and classifiers are gathered from recent works to enhance the understanding of the characteristics of preprocessing methods, features extraction techniques, and classifiers to guide future research directions and compensate for current research gaps.

1. Introduction

Fish classification (FC) is the act of identifying and recognizing fish species and families relying on their features. It identifies and categorizes the target fish into species relying on the similarity with the representative specimen image (Ogunlana et al., 2015). This process is essential for feature extraction, pattern and contour matching, determination of behavioral and physical traits, and quality control of fish species (Bermejo, 2007). FC is considered helpful for fish population assessments and counting, monitoring ecosystems, and description of fish associations (Cabreira et al., 2009). Precise fish species recognition is vital because of the legal restrictions on fishing practices, especially when their existence is endangered or threatened.

Currently, notwithstanding its commercial and agricultural value, fish recognition is regarded as a highly complicated and multifaceted task (Ding et al., 2017; Hnin and Lynn, 2016; Al Smadi, 2016). Also, all types of solutions for automatic FC should consider several elements such as the orientation of fish and arbitrary size; variability of feature; changes in the environment; poor image quality; segmentation failures; imaging conditions; physical shaping (Ogunlana et al., 2015; Alsmadi et al., 2012, 2011a, 2019).

Research in FC can be traced back to 1994 (Castignolles et al., 1994). The authors attempt to automatically classify the fish images by using the off-line detection method with static thresholds for segmenting fish images that were captured by tapes of S-video and improve the contrast of images by the use of background lighting. Moreover, to classify the fish species a Bayes classifier was used after extracting twelve geometrical features from fish images. However, because of the insufficiency such as fish alignment close to each other, this work has not received much attention. Zion et al., (1999, 2000) pursued this research and reached optimistic results using moment-invariants when extracted several geometrical features from three fish species. Subsequently, many researchers were following on this topic and a significant amount of efforts were made to find the optimal FC method.

Later Lee et al. (2003) used the critical landmark points using Curvature Function (CF) analysis on the fish contour to extract the shape features such as Adipose-fin length and Anal-fin length to automatically identify fish species. These methods obtained good classification accuracy.

Also, Lee et al. (2008)) examined several shape descriptors, for example, line segments, polygon approximation, and Fourier descriptors, and CF analysis for fish images categorizing using the

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Peer review under responsibility of King Saud University.

Production and hosting by Elsevier

https://doi.org/10.1016/j.jksuci.2020.07.005
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Please cite this article as: M. K. Alsmadi and I. Almarashdeh, A survey on fish classification techniques, Journal of King Saud University – Computer and Information Sciences, https://doi.org/10.1016/j.jksuci.2020.07.005

critical landmark points features that were extracted from contour representation. However, the main difficulties of these methods (Lee et al., 2003, 2008) are that feature location and measurements sometimes cannot be located very accurately and are manually calculated. Moreover; more efficient methods for finding the essential landmark points are required.

Although FC based on extracted features from color signature and texture descriptors has attained significant success, nevertheless, the classification accuracy is still considerably influenced by feature variability and conditions of illumination (Alsmadi et al., 2019; Nery et al., 2005). Many researchers have shifted to use the combination between the extracted features from the shape and texture measurements because of its potential capabilities to enhance the FC accuracy (Badawi and Alsmadi, 2014; Alsmadi, 2019).

Recently, many researchers used the BP algorithm, Support Vector Machines (SVMs) for FC such as (Alsmadi, 2019; Sharmin et al., 2019). Also, Chhabra et al. (2020) employed a hybrid Deep Learning (DL) model and used a pre-trained VGG16 model for feature extraction, and Stacking ensemble model for detecting and classifying fish images. Many fields such as (Checcucci et al., 2019) are applying DL based methods, these methods have a great advantage over traditional algorithms in object classification and computer vision (Thorat et al., 2020). The performance of various classification systems was enhanced by combining DL methods, Deep CNN shows significant results in the image processing by using DL approaches for training large-scale datasets of fish images (Cui et al., 2020; Taheri-Garavand et al., 2020), and the classification accuracy of fish images has been significantly increased using the DL methods (Zheng et al., 2018; Miyazono and Saitoh, 2018). Moreover; DL algorithms can detect simple features easily like simple shapes, edges, ...etc (Chhabra et al., 2020; Sung et al., 2017). Also, they can detect features that human beings can't distinguish.

The most important stage of FC is the extraction of the features, it comprises two forms which are appearance-based (such as colors and textures) and geometric-based. In geometric-based feature extraction, the local features (local statistics and locations) such as fish mouth length, anal fin length, fish head angle, eye-end mouth angle, and caudal fin length are extracted from fish images. The appearance-based feature extraction characterizes the appearance information brought by different fish objects in the whole-fish or specific regions in a fish image. Next, in the feature selection step, a subset of relevant features will be selected to classify different fish images into species/families. Also, a learning algorithm is considered to be an essential process in which the fish image is categorized into families/species such as garden fish, food fish, poison fish, non-poison fish. The geometrically based feature extraction includes the length of the body, anal fin, caudal fin, dorsal fin, pelvic fin, and other components of fish. Also; the feature extraction based on appearance includes the color signature, gray texture, and other features. However, such features are sensitive to changes in scale, illumination levels, and noise.

According to the state-of-the-art literature (Ogunlana et al., 2015; Ding et al., 2017; Hnin and Lynn, 2016; Alsmadi et al., 2010a,b, 2011a,b, 2012; Badawi and Alsmadi, 2014; İşçįMEN et al., 2014; Badawi and Alsmadi, 2013; Singh and Pandey, 2014; Ali-Gombe et al., 2017), there is no such review study has done before about the preprocessing methods, features extraction methods, classification algorithms and the datasets that were used for FC. While this study presents a survey of diverse preprocessing methods, feature extraction methods, classifiers algorithms, and the datasets that were used for FC. This study will be important and beneficial for the agricultural domain and marine scientists and can be utilized to investigate the marine world. Thereby, it will help fisheries biologists to collect and process their data. Moreover; this study will be important and beneficial for the industrial field of fish such as the nutrition and canning factories which can utilize this research to classify fish into dangerous and non-dangerous families, to classify the dangerous fish families into predatory and poison fish families, and to classify the non-dangerous fish families into garden and food fish families.

This paper surveys over 80 papers that describe features extraction methods and classification algorithms of FC to answer three questions:

- What preprocessing methods are being used to improve the performance of the FC system?
- What methods are being used to achieve the extraction of robust features which are invariant under translation, scaling, and rotation?
- What algorithms are being used to classify fish images?

Based on the literature review, this paper generally concentrates on various FC techniques and methods with the main steps: firstly preprocessing, secondly feature extraction, and thirdly classification. Moreover; this work demonstrates the performance analysis of various FC techniques and their advantages, and provides important ideas for future FC research. However; this paper does not address video-based techniques.

In essence, besides the introduction section, this paper is organized as the following: Section 2 explores the methods related to the preprocessing, features extraction and classification algorithms for FC; section 3 discusses the dataset used for FC; section 4 evaluates the FC techniques performance using different charts and tables; section 5 provides the future research directions, and section 6 concludes this survey.

2. FC system

The FC system overview is demonstrated in Fig. 1. It includes the three main steps of FC firstly fish image preprocessing, second feature extraction, and finally classification step.

2.1. Preprocessing

The process of preprocessing can be used for improving the FC system performance and it is carried out before the process of feature extraction (Hnin and Lynn, 2016; Alsmadi et al., 2012). The preprocessing of images comprises of a variety of processes such as contrast adjustment, converting the fish image into a grayscale image, scaling, suppressing background noise, highlighting the target area of the image and eliminating noise. There are, also, enhancement processes to improve the reliability and efficiency of the features extraction (Alsmadi et al., 2012).

The processes of scaling and cropping were done for the fish image where the ventral part of the fish is considered as the midpoint, also the other essential fish components are physically included (Alsmadi et al., 2012, 2010; Hu et al., 2012). Sobel edge operator and some morphological operations are performed to get the binary image from the fish image (Amanullah Baloch et al., 2017). Where the Sobel operator is a discrete differentiation operator, that computes an estimation of the image intensity function gradient (Vincent and Folorunso, 2009). The advantages of Sobel edge operator are its simplicity and detection of edges and their orientations, but its drawback is the sensitivity to noise.

Grabcut's algorithm was used for image background removal (Hernández-Serna and Jiménez-Segura, 2014). Morphological operations are executed on the fish image to acquire the binary image (Abdeldaim et al., 2018). The authors in (Abdeldaim et al.,

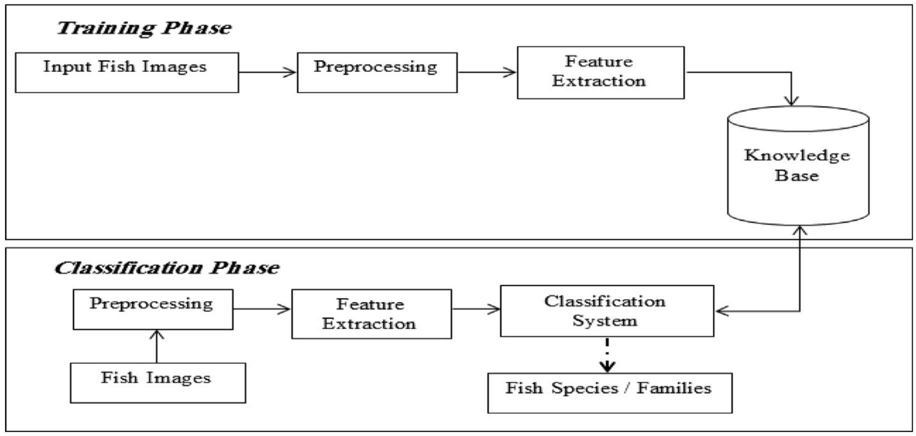

Fig. 1. FC system architecture.

2018) used Grabcut algorithm to segment fish object from image background and some morphological operations to remove unwanted shapes from images, which are: opening operator which removes the foreground object boundaries, and it is beneficial for eliminating small white noises, and closing operator which is beneficial in small black points closing on the object or small holes closing on the foreground objects (Abdeldaim et al., 2018). The nearest-neighbor method is utilized for input images resizing which provides the image's smoothness.

Image Filtration is also another important step in the preprocessing phase. The main goal of image filtration is to enhance the knowledge of the image's information to obtain an enhanced image from the unclear input image. Image Filtration was applied for image smoothing and variations reduction in the fish images (Alsmadi et al., 2012; Sayed et al., 2018) using the median filter and to achieve an enhanced fish image (Hernández-Serna and Jiménez-Segura, 2014; Sayed et al., 2018). The anchor points method is utilized for the distance and angle measurement extraction which is more robust to characteristic differences in the FC system and it enhance the accuracy of the potential local geometric features (Ogunlana et al., 2015; Badawi and Alsmadi, 2014; Alsmadi et al., 2010, 2011, 2012, 2019; Saitoh et al., 2016; Kutlu et al., 2017; Al Smadi, 2016).

Object detection is a preprocessing method and it uses the Viola-Jones algorithm (VJ) to detect and identify the fish object from the input image (Matai et al., 2010). The closing and opening operations of mathematical morphology are used (Yao et al., 2013) to separate the target and background, followed by border extraction to get a more complete fish outline. The normalization process is the preprocessing technique that is applied to resize the fish image to the adopted size and to rotate the fish image to its standard position to eliminate the differences between dataset images, these differences are problematic for features calculation (Alsmadi et al., 2012; Miyazono and Saitoh, 2018; Saitoh et al., 2016). Also, normalization in the preprocessing stage eliminates the variation problems in the images. One of the most important types of preprocessing methods is the Region of Interest (ROI) method that is used to determine the region of the fish image (for example eye pupil or forehead region) which is used to differentiate between fish species/families (Amanullah Baloch et al., 2017; Işçimen et al., 2018). Histogram equalization is one of the most common enhancement approaches in FC, The histogram equalizer was used to equalize the color of fish image (Mokti and Salam, 2008). This technique is utilized to overcome the variations in illumination. It is used for increasing the fish image contrast, to measure the quality of the fish image, and to enhance the distinction between the intensities.

The preprocessing step is usually performed before features are extracted from the fish image, it is necessary to enhance the readability of the fish image, remove noise, resize image g, etc. The preprocessing step makes the feature extraction step more reliable, accurate, and has a significant impact on classification performance. In FC, many preprocessing methods are utilized, however, the cropping process and ROI are the most appropriate since it detects the fish characteristics precisely. Also, the anchor point's method is an essential preprocessing technique for FC because it increases the accuracy of the potential local geometric features. The image filtration is also an important preprocessing technique for FC to achieve an improved fish image. Finally; these preprocessing methods assisted to achieve high FC accuracy as in (Ogunlana et al., 2015; Badawi and Alsmadi, 2014; Alsmadi et al., 2010, 2011, 2012, Hu et al., 2012; Saitoh et al., 2016; Mushfieldt et al., 2012; Al Smadi, 2016).

2.2. Feature extraction

The next step in the FC process is feature extraction. It involves depicting and finding important positive features inside an image for further steps of processing. In image processing, feature extraction is an important stage, while it highlights the change from graphic to implicit data depiction. After that, the data depiction is used as the classification input. The methods of feature extraction are classified into five types namely: shape feature-based method, local and global feature-based method, color feature-based method, texture feature-based method, and combination-based feature extraction method.

The shape feature-based methods are described as the following: Moment-Invariants (MI) combined with geometrical considerations which are texture descriptors for feature extraction. Hence, the method was insensitive to fish size aside from being two-dimensional and located within the view field of the camera (Zion et al., 1999). Curvature Scale Space (CSS) is also a shape descriptor that can be utilized for feature extraction. Generally, in the CSS, the target object (foreground part) is transformed into a map of Curvature Scale Space (CSS). Next, the CSS map is transformed into a Circular Vector (CV) map to enable rotation to an invariant matching (Sze et al., 1999). CF analysis was used to extract the shape features, and to locate critical landmark points upon the fish contour to extract the shape features (Lee et al., 2003, 2008). FishID algorithm is an accurate and simple real-time contour matching technique specifically for applications containing fish species classification. The technique correctly determines the species with greater than 90% accuracy using the size and shape features, FishID algorithm was the improvement of a more accurate classification technique (Lee et al., 2008); the authors in (Lee et al., 2003, 2008) mentioned fish shape as the most dependable general characteristic when making a distinction between species.

Landmarks/anchor points method is one of the most used methods to extract the size and shape features (İşçįMEN et al., 2014; Kutlu et al., 2017). Where fish size and shape features are extracted using distance and angle measurements from the determined Landmarks/anchor points (Alsmadi et al., 2011, 2019). The authors in (Lee et al., 2003; Alsmadi et al., 2010) reported the effectiveness of the landmark/anchor points method in finding all the crucial points for FC according to shape characteristics. Furthermore, to improve the classification accuracy, the authors proposed the extraction of more landmark/anchor points features particularly in the situation where there are more species to be classified. For example, a comparison of the width of the dorsal fin, as well as the length between the dorsal fin and adipose fin, should be taken into account since the association of these two differs for various species.

For feature selection, there is rarely a good way to choose appropriate Feature Subset Selection (FSS) algorithms for various dataset types. Therefore; through selecting suitable attributes, the FSS algorithm automatic recommendation is a useful step for efficient FC (Hnin and Lynn, 2016). A combination based Features Selection algorithm is used for feature selection, the algorithm focuses on enhancing the performance of the classifier using unknown data (Hnin and Lynn, 2016). A scheme for fish image segmentation and fish morphological features indicators measurements was proposed based on the Mask R-CNN algorithm (Yu et al., 2020). The scheme that was proposed effectively segmented the fish body in complex and pure backgrounds with prominent results.

Single Value Decomposition (SVD) was used to extract the features from the fish image which is a factorization of a complex or real matrix, a moving overlapping window divided the fish image into fifteen image blocks, as the window moves from head to tail region of the grey-level fish image, the feature values are extracted from every area occupied by a window and combined to form feature vector, then the feature vector is passed as input data to ANN algorithm to classify fishes into different species (Daramola and Omololu, 2016). The non-rigid part model efficiently discovers discriminative parts of fish by adopting saliency and relaxation labeling. Consequently; discrimination of fish parts, separation, and fitness are considered to be meaningful in identifying in an unsupervised manner representation of fish body parts (Chuang et al., 2016).

Scale Invariant Feature Transform (SIFT) is an algorithm for feature detection in computer vision and is used to describe and detect local features in digital images (Karami et al., 2017). It locates and extracts certain key points of the objects from a set of reference images and then provides them with measurable information (so-called descriptors) which can be used for object recognition (Fouad et al., 2013). The descriptors are assumed to be invariant against different transformations which could make the images that represent the same object(s) look different. SIFT is used for matching fish images, by finding the important key points in two fish images and matching those key points against other fish images. Mainly; SIFT used dimensionality reduction to find these key points. Also, it is robust to rotation, variations in scale, and illumination in the test set images (Matai et al., 2010).

Salp Swarm Algorithm (SSA) is a random population-based algorithm that was proposed by Mirjalili et al. in (Mirjalili et al., 2017), it mimics the salps swarming mechanism when looking for food in oceans. Salps in heavy oceans usually form a swarm known as a salp chain, the leader in this algorithm is the salp at the front of the chain and the rest of the salps are called followers. Like the other swarm-based techniques, the salps position is identified in an s-dimensional search space, where s is the variables number of certain problems. Thus, the all salps position is stored in a 2D-dimensional matrix (z). In the search space, it is also assumed that there is a food source called P as a target for the swarms. SSA is used for fish image segmentation and feature extraction, for further explanations about the mathematical description of SSA please refer to (Ibrahim et al., 2018). The Simple Linear Iterative Clustering (SLIC) method was formulated for the segmentation process with initial parameters optimized by the SSA to generate nearly uniform and compact super-pixels (Ibrahim et al., 2018). SLIC is among the most essential super-pixels segmentation algorithms which require low computational power (Ibrahim et al., 2018).

The local and global feature-based methods are elaborated as follows: Local features can generate better results for fish image segmentation compared to global features because different fish species have different textures, color signatures, and shape features in their body parts. Fish Image Segmentation Algorithm (FISA) is used to separate the fish object into three segments body part (head, abdomen, and tail parts) (Amanullah Baloch et al., 2017). Speeded Up Robust Features (SURF) are partly inspired by the SIFT which are descriptors that were used for locating and recognizing, tracking, and extracting points of interest of the objects. SIFT and SURF algorithms are local feature descriptors which extract the local features such as pixel gradients and key point localization from Tilapia fish images (Fouad et al., 2013, 2016). A fish detection method based on the BAT optimization algorithm was proposed (Fouad et al., 2016). Other work used SURF for local feature extraction (Freitas et al., 2013). CNN was used to extract and classify the fish images with low- resolution (Rachmatullah and Supriana, 2018). Also, the data augmentation was employed to handle an imbalance within the data. The authors in (dos Santos and Gonçalves, 2019) used two convolutional layers combined with data augmentation and dropout, the accuracy of the proposed model was 99.7% on testing data. A CNN was used to classify the Pantanal fish species and improve the classification of fish species with similar characteristics. The proposed CNN was formed of three branches that classify the fish species, family and order, the obtained results based on unlimited image dataset showed that the proposed CNN offered superior results compared with traditional methods (dos Santos and Gonçalves, 2019). A computer vision method based on DL techniques was proposed in (Siddiqui et al., 2018), in order to avoid the need for a large number of training data, a cross-layer pooling algorithm using a pre-trained CNN as a generalized feature detector was introduced. Then, the SVM was used to perform the classification on test data using the features calculated from the proposed method with an accuracy rate of 94.3% for fish species (Siddiqui et al., 2018). An improved transfer learning method and squeeze-and-excitation networks was presented in (Qiu et al., 2018) for fine-grained fish image classification using small scale and low-quality datasets. The proposed method accomplishes better results in fish image classification.

The color feature-based methods are elaborated as follows: Color Space is another descriptor that is used to extract the features for FC (Hu et al., 2012; Işçimen et al., 2018; Freitas et al., 2013). Feature sets for both color spaces (RGB and HSV) are extracted using the red, green, blue components of the RGB color space and hue, saturation, value components of the HSV color space are used separately for FC (Işçimen et al., 2018). Grabcut algorithm is a foreground extraction algorithm that can be used when background and foreground color distributions are not well separated. Grabcut Algorithm relies on graph cuts and operates by determining a

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bounding box surrounding the object to be segmented. Thus; the whole image is used as a bounding box and the algorithm approximates the target object and background color distribution. The Grabcut algorithm is applied to detect and segment fish from natural images even with different circumstances using RGB color space (Abdeldaim et al., 2018). RGB is suitable for color display but it is a poor choice for color scene analysis because of the high correlation among I_R; I_G, and I_B (Hu et al., 2012). Paschos found that HSV performs better for color texture classification (Paschos, 2001). Therefore; ten extracted color features using RGB and HSV color spaces were extracted for fish image classification (Hu et al., 2012), these features are R mean, G mean, B mean, RGB mean, RGB standard deviation, H mean, S mean, V mean, HSV mean and HSV standard deviation. Other work used several color feature extraction methods which are Bag of Visual Words, HSV and RGB color histograms, Bag of features and colors, Bag of colored words, and a bag of colors (BoCW) (Freitas et al., 2013).

The texture feature-based extraction techniques are elaborated as follows: The Gray-level co-occurrence matrix (GLCM) is a feature extraction texture descriptor and it considers the spatial relationships of pixels and characterizes the texture of the fish image through calculating the frequency of occurrence of specific values and specific spatial relationship of pixel pairs in an image, which creates a GLCM, then statistical measures are extracted from the GLCM (Alsmadi et al., 2011). GLCM is applied to extract color signature using RGB color space and color histogram technique from the ventral part of the fish object. Then, three statistical features which are standard deviation, homogeneity, and energy were calculated (Alsmadi et al., 2011). Another work (Alsmadi et al., 2010) used GLCM to extract color texture from the colored fish image, the fish image was divided into 4 * 4 blocks. Then, for each block six statistical features which are average, dissimilarity, standard deviation, homogeneity, contrast, and energy were calculated using GLCM. GLCM gives a good degree of accuracy in discriminating color signature (Alsmadi et al., 2011) and color texture (Alsmadi et al., 2010). Another work (Wishkerman et al., 2016) used GLCM to extract texture features after converting the color fish image into a grayscale image followed by data dimension reduction procedures.

Gabor Filter (GF) is a feature extraction texture descriptor and it is used for edge detection, it relies on the orientation representations and frequency, it is employed in several pattern recognition applications i.e., iris identification, hand vein identification, and fingerprint identification (Badawi and Alsmadi, 2014). Four features (contrast, standard deviation, mean, and homogeneity) were calculated for FC using the GF output image (Al Smadi, 2016; Badawi and Alsmadi, 2014). GF was also used to extract texture features from fish Images (Kumar, 2018). GF can be defined as a sinusoidal plane of particular orientation and frequency, modulated by a Gaussian envelope.

The combination-based feature extraction methods are described as follows: Analyzing a series of texture, color, and shape of the fish image and combining their variations became the fundamental step to discriminate between the fish species and enhance the classification accuracy rate (Alsmadi et al., 2012; Badawi and Alsmadi, 2014; Sharmin et al., 2019; Kaya et al., 2018). The combined principal component analysis weighs the texture and shape based on the generalized variances of the two types of variation, then the weights were used to discriminate between the three fish species (Larsen et al., 2009). A large set (47 different features) of combined extracted shape measurements (19 features), size measurements (4 features), texture measurements (16 features), and color signature (8 features) from different fish species were extracted for FC. These combined features significantly improved the performance of FC (Nery et al., 2005). The hybrid Mean-shift with Median-cut algorithms have been used to obtain more region boundaries and eliminate unwanted and small regions. Therefore; LUV color space was used to ensure the isotropy of the feature space and then the fish contour was detected using the Canny edge method (Mokti and Salam, 2008). A general FC was performed using the combination between significant extracted anchor points (using distance and angle measurements), texture and statistical measurements to classify the fish images into dangerous and non-dangerous families, classifying the dangerous fish families into Predatory and Poison fish family, as well as classify the non-dangerous fish families into garden and food fish family (Al Smadi, 2016; Alsmadi et al., 2019; Badawi and Alsmadi, 2014). Shape- and texture-based fish image recognition system (FIRS) used the simple shape characteristics, color, and fish size features for the classification process (Pornpanomchai et al., 2013). The deep Convolutional Neural Network (CNN) method is used to extract feature maps from noisy fish images (Ali-Gombe et al., 2017). Texture-based features and shape-based features were used to extract 22 texture features using GLCM, also, 16 local and shape features were extracted from the segmented fish image. Then, the binary crow search algorithm (BCSA) is employed as a feature selection algorithm based wrapper method to select the optimal feature subset (Sayed et al., 2018). RGB, HSV, CIELa*b*, CIE 1931 XYZ color spaces, and normalized RGB values were used to extract twenty-three color features, also four texture features (Contrast, Energy, Homogeneity, and Correlation) were extracted using GLCM (Saberioon et al., 2018). A series of 15 morphological, geometrical, and texture features were extracted from the fish image using shape measurements, statistical approximation, and two-dimensional Cartesian moments (Hernández-Serna and Jiménez-Segura, 2014). In Takeshi et al. (Saitoh et al., 2016), Seven geometric features were extracted using four feature points and several texture features were extracted using Histogram of Oriented Gradient (HOG), LBP, GLCM, Discrete Cosine Transformation (DCT), Run Length Matrix (RLM), and Shape-pass Nonlinear Filter (NF).

Feature extraction involves transforming the original data to a data set contains the most discriminatory information, this information (denoted by a reduced number of variables) will most meaningfully or efficiently represent the information that is important for analysis and classification (Abhang et al., 2016). As can be observed from the above-reported survey papers, the fish shape characteristics appear to be the most commonly used features for FC. As shown in several works (Alsmadi et al., 2012, 2019; Lee et al., 2008; Sayed et al., 2018), the various information of shape characteristics is highly essential in the improvement of fish recognition accuracy and is invariant to scaling, translation, and rotation. This owes to the fact that fish image can be captured from diverse locations and angles, and with different sizes. For instance, subtle differences in shape that are based on each species can be determined through analysis of distinguishable landmarks/anchor points, for example, fins insertion, nose tip, as well as margin of operculum which illustrate the shape of fish's body and head. Moreover; the analysis of a series of textures, colors and shapes of the fish image and their combined extracted features has become the fundamental step to utilize their ability to discriminate between the fish species and enhance the classification accuracy rate. From the results, it appears that fish shape feature and the combination of features are the most dependable common characteristics in ascertaining the fish's species or families.

2.3. Classification

Classification is the final step of the FC system, the fish is classified by the classifier into either families such as dangerous, non-dangerous, predatory, poison, garden, and food families or into species such as Ariomma brevimanum, Acanthurus grammoptilus and Acropoma lecorneti.

Table 1
FC techniques with their classification algorithms.

Author	Preprocessing Method	Feature Extraction Method	Classification Algorithm
Hernández-Serna and Jiménez-Segura (2014)	Grabcut's algorithm, smooth, median filters	Geometrical, morphological, texture features	Neural Networks
Zion et al. (1999)	Normalization	Moment-Invariants (MI)	Average test-set classification error
Lee et al. (2003)	Fish detection	CF, distance measurements	MDC
Lee et al. (2008)	Fish detection	CF, landmark points	TADA
Mokti and Salam (2008)	Histogram equalizer	Canny edge method, hybrid of mean-shift and median-cut	Not specified
Nery et al. (2005)	Not reported	Minimum Enclosure Rectangle (MER), Aspect ratio, squared perimeter, moments, co-occurrence matrix, YUV and HIS color models, feature ranking approach	Bayesian classifier
Wishkerman et al. (2016)	Resizing, Cropping	GLCM	PCA and LDA
Hossain et al. (2016)	GMM	PHOW	SVM
Alsmadi et al. (2010)	Median filter and anchor points detection	distance and angle measurements	BP algorithm
Alsmadi et al. (2010)	Fish region cropping	GLCM	BP algorithm
Alsmadi et al. (2011)	Fish region cropping	GLCM, color histogram	BP algorithm
Badawi and Alsmadi (2014)	Anchor points detection	GF, distance and angles measurements, statistical Measurements	GAILS-BPC
Alsmadi et al. (2011)	Anchor points detection	distance and angles measurements	HGAGD-BPC
Kutlu et al. (2017)	Anchor points detection	Distance measurements	Nearest Neighbour algorithm
Hnin and Lynn (2016)	Mean imputation	FSS algorithms	SVM
İşçiMEN et al. (2014)	Not reported	Landmarks/anchor points detection, Euclidean network technique, Quadratic network technique, Triangulation technique	Naive Bayesian classifier
Hu et al. (2012)	Fish region cropping, resizing the fish image	GH, GLCMs, Wavelet Transform, RGB and HSV color Features	multiclass SVM
Ogunlana et al. (2015)	Anchor points detection	Optimal Separating Hyper-plane (OSH), The Margin of Separation (MS)	SVM
Daramola and Omololu (2016)	Converted color fish images to grey-level image	SVD	BP algorithm
Qin et al. (2016)	Sparse and low-rank matrix decomposition, resizing the fish image	Deep architecture, binary hashing, spatial pyramid pooling, PCA	linear SVM classifier
Kratzert and Mader (2018)	Fish detection	FishCam monitoring system	CNN
Freitas et al. (2013)	Resizing fish image	SURF, Bag of visual words, HSV and RGB color histograms, bag of features and colors, bag of colors and Bag of Colored Words (BoCW)	SVM, KNN, DT
Mushfieldt et al. (2012)	ROI and fish region cropping	Mouse click, HSV color space, adaptive threshold, Histogram representation,	SVM
Chuang et al. (2016)	Not reported	Non-rigid part model	Hierarchical partial classifier algorithm
Matai et al. (2010)	Fish detection	SIFT	PCA algorithm
Saitoh et al. (2016)	Anchor points detection, normalization	LBP, HOG, DCT, GLCM, RLM, shape-pass NF, distance and angles measurements	RF
Miyazono and Saitoh (2018)	Image size normalization, annotated image method	Plotting method, Gaussian filter	CNN
Pornpanomchai et al. (2013)	Size adjustment, grayscale conversion, black and white conversion, noise removal, edge detection and object segmentation.	EDM	ANN
Jäger et al. (2016)	Fish detection, blob detection method	CNN features, binary SVM classifier	multiclass SVM
Fouad et al. (2013)	Not reported	SIFT, SURF	ANN classifier SVM algorithm
Al Smadi (2016)	Converted color fish images to the grey-level image, anchor points detection	GF, distance and angles measurements, statistical measurements	BP algorithm, GAGD-BPC
Ali-Gombe et al. (2017)	Isolating individual fish, resizing the fish image	VGG-16 model, transfer learning model	Deep CNN
Sayed et al. (2018)	Image enhancement using the median filter	BCSA, wrapper method	SVM and DT
Kartika and Herumurti (2016)	Separate the fish object from the background, resizing the fish image	RGB and HSV colors features	SVM and Naive Bayes algorithm
Chen et al. (2017)	Fish detection, pose estimation and alignment	Image-level and instance-level classification.	CNNs
Andayani et al. (2019)	Cropping, scaling, ROI, grayscale color mode and HSV color mode	Geographical invariant moment features, Gray Level Co-occurrence Matrix texture features and HSV color feature extraction	Probabilistic Neural Network
Alsmadi et al. (2019)	Grayscale conversion, anchor points detection, fish region cropping	GLCM, distance and angles measurements, statistical measurements	MA-B Classifier
Alsmadi (2019)	Fish region cropping, anchor points detection	GLCM, distance and angles measurements	GTB Classifier
Sharmin et al. (2019)	Resizing fish image, conversion to grayscale and histogram formation	RGB and HSV colors features, geometric measurements, GLCM	SVM
Islam et al. (2019)	Not reported	Hybrid Local Binary Pattern (HLBP)	SVM
Chhabra et al. (2020)	Not reported	Pre-trained VGG16 model	Stacking ensemble model

In binary images Moment Invariants (MI) are connected regions properties that are invariant to scale, rotation and translation. They are beneficial since they describe a set of region properties that are simply calculated to be used for part recognition and shape classification. The MI method is used for estimating fish size and recognition of three fish species (Zion et al., 1999). Also, Euclidean distance metric is utilized for purpose of classification, it uses the similarity score matrix and the normalized score for Euclidean distance estimation, The Euclidean distance measures the similarity between every feature of an unknown fish image and every feature of each training data set in the FIRS (Pornpanomchai et al., 2013). Minimum Distance Classifier (MDC) is an FC distance-based classifier that uses the estimation of the distance between the feature vectors in the database and the feature vector of the test fish (Lee et al., 2003). Turn Angle Distribution Analysis (TADA) is a matching method that allows the contour for the current fish image to be matched against species-specific contours in the FishID database (Lee et al., 2008).

The extracted fish features were fed into a well-designed 3-layer neural network classifier that is trained by a Back Propagation (BP) algorithm for the FC task (Hnin and Lynn, 2016; Alsmadi et al., 2010a,b, 2011a,b; Hernández-Serna and Jiménez-Segura, 2014; Daramola and Omololu, 2016; Pornpanomchai et al., 2013). A Hybrid Memetic Algorithm (Genetic Algorithm and Great Deluge Local Search) together with Back-Propagation Classifier (HGAGD-BPC) and Back-Propagation Classifier (BPC) is used also for FC (Alsmadi et al., 2011) and another work used the similar classifier for fish image classification (Al Smadi, 2016). A hybrid meta-heuristic algorithms (genetic algorithm with iterated local search) with back-propagation algorithm (GAILS-BPC) for generic fish (classifies the fish images into families and species) (Badawi and Alsmadi, 2014). A hybrid meta-heuristic algorithms (Genetic Algorithm with Simulated Annealing) with back-propagation algorithm (MA-B Classifier) for generic fish (classifies the fish images into families and species) (Alsmadi et al., 2019). Inserting a local search algorithm to the genetic algorithm (such as iterated local search and Great Deluge Local Search) enhances the exploitation process rather than the exploration process. The Metaheuristic Algorithms (MA) successfully improved the BP performance by improving and optimizing the weights of the back-propagation algorithm.

The Support Vector Machine (SVMs) is utilized for regression and classification of high dimensional data sets with excellent results (Fouad et al., 2013). Support Vector Machine (SVM) is one of the classification techniques that was used for FC based on the number of features extracted from the fish image dataset (Hnin and Lynn, 2016; Fouad et al., 2013; Hossain et al., 2016; Islam et al., 2019). Also, SVM is used for the elimination of the limitations of some existing techniques such as K-mean Clustering, K-Nearest Neighbor (KNN), and Neural Network and enhancing the fish species classification (Ogunlana et al., 2015; Kutlu et al., 2017), also multiclass SVM is used for fish species classification (Hu et al., 2012). SVM and decision trees (DT) were used for fish species classification, the fish species are classified based on either their class or based on their order (Sayed et al., 2018). A linear SVM classifier is used for accurate underwater live fish recognition (Qin et al., 2016). Other work used three types of classifiers which are SVM, KNN, and Decision Tree for FC (Freitas et al., 2013).

Four different classifications (Random Forest (RF), SVM, Logistic regression (LR), and KNN) methods were used to evaluate fish diets. The SVM with radial based kernel provided the best classifier with correct classification rate (Saberioon et al., 2018). Naive Bayesian classifier is one of the most efficient and effective machine learning algorithms and it was used to classify 7 fish families and 15 fish species (İşçįMEN et al., 2014).

The hierarchical partial classifier algorithm was utilized in the presence of multiple and partial path classifications and evaluated with both NOAA Fisheries and F4K datasets (Chuang et al., 2016). Principal Component Analysis (PCA) algorithm is a statistical method under the broad title of factor analysis and it was used to identify the fish species (Matai et al., 2010). PCA and Linear Discriminant Analysis (LDA) was used to compare and analyze the effectiveness of discrimination and classification procedures of sole skin textural descriptors (Wishkerman et al., 2016).

Deep CNN relies on an untrained VGG-16 network, the network model contains 5 blocks of 13 convolution layers and 3 fully connected layers, and CNN is used for FC using noisy fish images. Other, CNN is composed of two convolutional layers, which are a pooling layer, and a fully connected layer. It is used for fish species recognition using the fish images (Miyazono and Saitoh, 2018; Choi, 2015; Rekha et al., 2019). Other work used a CNN together with fish species classification, based on the standard classifiers like SVM and KNN, it was trained on the features extracted from fish images by the CNN in supervised DL (Salman et al., 2016). Another work used two different CNN architectures "scaled-down VGG-16" and "traditional VGG-16" model for FC (Thorat et al., 2020).

The Bayesian classifier is used for FC (Nery et al., 2005), the effectiveness of the Bayesian classifier has been proved in various pattern classification problems (Nery et al., 2005). RF is an ensemble training algorithm that constructs multiple decision trees, RF can be used for regression, unsupervised learning, and classification. RF was applied for fish image classification with a number of trees M experientially set to 200 and the maximum depth of each tree D experimentally was set to 10 (Saitoh et al., 2016).

The FC techniques with their classification algorithms are shown in Table 1; it involves the algorithms which are utilized for the 3 steps which are preprocessing, feature extraction, and classification. Table 1 demonstrates that the Fish image resizing, fish detection, landmark/anchor points and image cropping methods as the most commonly used methods in the preprocessing step. For feature extraction; the most commonly used methods are distance measurements, angles measurements, GLCM, Gabor filter, SIFT, and SURF. Most of the feature extraction methods rely on a combination of features such as combined extracted shape, size, texture, and color signature features. For FC; the most commonly used algorithms are SVM, BP algorithm, HGAGD-BPC, GAILS-BPC, Bayesian classifier, and CNN. Moreover; SVM, HGAGD-BPC, and GAILS-BPC are mostly utilized, they provide the best performance compared to other classifiers.

3. Database description

Table 2 shows the various databases that were used for FC experiments such as Global Information System (GIS) on Fishes and Fish4- Knowledge (F4K) databases. The used databases contain a different number of species, families, images, and image resolutions.

In most of the experiments, the database that was used is in (Al Smadi, 2016; Alsmadi et al., 2011a,b, 2010; Badawi and Alsmadi, 2014, 2013) followed by the database used in (Chuang et al., 2016; Qin et al., 2016). The databases in (Alsmadi et al., 2012, 2011a,b, 2010) contain 20 fish families with a different number of fish images (320, 350, and 610) and every image has 512 * 512 pixels resolution.

Compared to other research fields there is no standard scientific benchmark dataset for FC research and its one of the limitations for the researchers in this domain, for example; most of the authors used different datasets, some of them used self-collected datasets and some of them mentioned the number of fish families/species

Table 2
FC Databases description.

Author	Origin	# of Families or Species	No. of images	Size	URL
Hasija et al. (2017)	F4K	10	840	Not reported	http://homepages.inf.ed.ac.uk/rbf/Fish4Knowledge/
Kaya et al. (2018)	F4K	3	130	Not reported	http://groups.inf.ed.ac.uk/f4k/
Islam et al. (2019)	BDIndigenousFish2019	8	2610	3968 * 2796	https://github.com/falvee/BDIndigenousFish2019
Zion et al. (1999)	Not reported	3	146	768 * 576	Not available
Nery et al. (2005)	Brazil	6	99	Not reported	Not available
Hossain et al. (2016)	Not reported	15	20,000	68 * 87	http://www.imageclef.org/lifeclef/2015/fish
Alsmadi et al. (2010)	Malaysia	20 fish families	350	512 * 512	https://www.fishbase.se/home.htm
Alsmadi et al. (2010)	Malaysia	20 fish families	610	512 * 512	https://www.fishbase.se/home.htm
Alsmadi et al. (2011)	Malaysia	20 fish families	610	512 * 512	https://www.fishbase.se/home.htm
Badawi and Alsmadi (2014)	GIS on Fishes	24 fish families	320	512 * 512	https://www.fishbase.se/home.htm
Alsmadi et al. (2011)	Malaysia	20 fish families	610	512 * 512	https://www.fishbase.se/home.htm
Hu et al. (2012)	China	6	90	512 * 512	Not available
Ogunlana et al. (2015)	Nigeria	2 families	150	20 * 20	Not available
Qin et al. (2016)	F4K database	23	27,370	47 * 47	http://groups.inf.ed.ac.uk/f4k/
Kratzert and Mader (2018)	ImageNet dataset	10	8099	Not reported	http://www.image-net.org/challenges/LSVRC/
Freitas et al. (2013)	AQUARIO28E40I dataset	28	1120	256 * 256	https://pistori.weebly.com/datasets.html
Mushfieldt et al. (2012)	knowledge database	20	200	720 * 576	https://bddatabase.net/us/theme/8529/
Chuang et al. (2016)	F4K database	15	26,418	200 *200	http://groups.inf.ed.ac.uk/f4k/
Matai et al. (2010)	Not reported	5	35	Not reported	https://swfsc.noaa.gov/
Saitoh et al. (2016)	Japan	129	2580	692 * 425	Not available
Miyazono and Saitoh (2018)	Japan	50	1000	256 * 256	Not available
Pornpanomchai et al. (2013)	FIRS database	30	900	800 * 600	https://www.fishbase.in/search.php
Jäger et al. (2016)	Not reported	15	20,000	320 * 240	https://www.imageclef.org/lifeclef/2016/sea
Abdeldaim et al. (2018)	Australia	25 fish families	270	256 * 256	http://fishesofaustralia.net.au/
Al Smadi (2016)	GIS on Fishes	24 fish families	320	512 * 512	https://www.fishbase.se/home.htm
Ali-Gombe et al. (2017)	Not reported	Not reported	3777	224 * 224	https://www.kaggle.com/c/the-nature-conservancy-fisheries-monitoring
Sayed et al. (2018)	Not reported	24 fish families	270	Not reported	https://www.fishbase.se/identification/RegionSpeciesList.php?resultPage = 55&c_code=356
Kartika and Herumurti (2016)	Not reported	9	281	50 * 100	https://br.pinterest.com/pin/810929476635332031/
Chen et al. (2017)	NCFM dataset	Not reported	4777	640 * 360	https://www.kaggle.com/c/the-nature-conservancy-fisheries-monitoring
Zheng et al. (2018)	Kaggle dataset	8	Not reported	Not reported	https://www.kaggle.com/c/the-nature-conservancy-fisheries-monitoring
Alsmadi et al. (2019)	GIS on Fishes	24	400	512 * 512	https://www.fishbase.se/home.htm
Alsmadi (2019)	GIS on Fishes	24 fish families	500	512 * 512	https://www.fishbase.se/home.htm
Rachmatullah and Supriana (2018)	Fish CLEF 2015	15	Not reported	408 * 171	http://www.imageclef.org/lifeclef/2015/fish
Qiu et al. (2018)	Croatian fish Dataset	12	794	Not reported	http://www.inf-cv.uni-jena.de/fine_grained_recognition.html#datasets

without mentioning its name, so this survey is helpful for other researchers since it shows the origin, number of species or families, number of images and the resolution of the images in datasets (as shown in table 2) that were used by the previous researchers in order to use it and make a fair comparison with their results.

4. Performance comparison

The performance comparison in this FC survey relies on the classification accuracy using the availability of preprocessing, feature extraction methods, databases used, main advantages, and contribution of the FC methods.

Table 3 shows the state-of-the-art methods that used the same dataset; for example, the authors in (Al Smadi, 2016) and (Badawi and Alsmadi, 2014) have used the same dataset but with different classifier algorithms, both works aim to classify the fish images into fish species and then classify them into non-dangerous and dangerous fish families and to recognize the non-dangerous into food and garden fish families and recognize the dangerous into poison and predatory fish families. Therefore; the meta-heuristic algorithms (Genetic algorithm With Iterated Local Search) and (Genetic Algorithm with Great Deluge algorithm) were used to significantly improve the classification accuracy of the BPC by tuning the parameters (weights) of the BP algorithm. The BP algorithm and hybrid GAILS-BPC in (Badawi and Alsmadi, 2014) outperformed the BP algorithm and GAGD-BPC in (Al Smadi, 2016) in terms of classification accuracy with a percentage of 82%, 85% and 81%,83.5% respectively.

The authors in (Alsmadi et al., 2011a,b, 2010) used the same dataset with the same classifier algorithm (BP algorithm) but each algorithm achieved different classification accuracy results. This is because every method used different preprocessing techniques, features extraction methods, number of features extracted, and number of neurons for each neural network layer.

The accuracy rates of the various FC methods are shown in Fig. 2, the x-axis represents the FC methods names, and the y-axis represents the accuracy percentages achieved by the FC techniques. The accuracy of every method is analyzed using data from its paper, so the mean accuracy rate is calculated. The techniques such as FSS algorithms with the SVM classifier achieve higher accuracy. Deep architecture, Binary hashing, Spatial Pyramid Pooling, PCA descriptors with the linear SVM classifiers achieve a higher accuracy rate. Somehow, the number of fish images, species, and families are crucial as well, aside from the rate of classification. The substantial increase in the number of fish images and the number of families will necessitate the use of a combined method. As an example, the method in (Lee et al., 2003) was tested on 22 fish images belonging to 9 species and it generated a high rate of

Table 3
Performance analysis of FC techniques using the same datasets.

Author	Origin	# of fish families	#. Of images	size	Algorithm	Classification accuracy
Al Smadi (2016)	GIS on Fishes	4 Dangerous families, 4 Poison families and 16 non-poison families	320	512*512	BP algorithm and GAGD-BPC	81% 83.2%
Badawi and Alsmadi (2014)	GIS on Fishes	4 Dangerous families, 4 Poison families and 16 non-poison families	320	512*512	BP algorithm and GAILS-BPC	82% 85%
Alsmadi et al. (2010)	GIS on Fishes	16 non-poison families and 4 poison families	350	512*512	BP algorithm	86%
Alsmadi et al. (2010)	GIS on Fishes	16 non-poison families and 4 poison families	610	512*512	BP algorithm	84%
Alsmadi et al. (2011)	GIS on Fishes	16 non-poison families and 4 poison families	610	512*512	BP algorithm	84%
Alsmadi et al. (2011)	GIS on Fishes	16 non-poison families and 4 poison families	610	512*512	BP algorithm and HGAGD-BPC	86% 96%
Alsmadi et al. (2019)	GIS on Fishes	16 non-poison families and 8 poison families	400	512*512	BP algorithm and MA-B Classifier	82.25% 90%
Alsmadi (2019)	GIS on Fishes	16 non-poison families and 8 poison families	500	512*512	BP algorithm and GTB Classifier	82.1% 87%

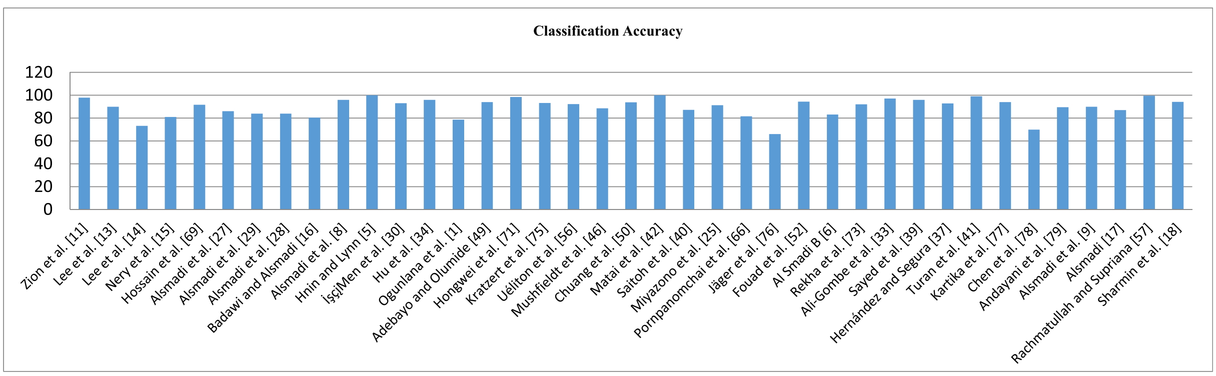

Fig. 2. Classification accuracy rate of various FC techniques.

recognition. On the other hand, 350 fish images belonging to 20 fish families were tested on other combined methods and a high rate of recognition was obtained (Alsmadi et al., 2011).

The analysis of the performance of the techniques of FC is demonstrated in Table 4. Author name, FC Algorithm name, database name, classification accuracy (%), Major advantages, and contribution of FC techniques are included in Table 4. The field of author name in the table denotes the various FC papers authors. The field of the FC algorithm name describes the algorithms used for the classification of fish images. The databases utilized in the FC papers are Self-collected, CNPq-Brazil, CLEF 2015, GIS on Fishes, F4K, AQUARIO28E40I dataset, knowledge database, Collected by Benson et al. (2009) database, rockfish images collected in situ by an ROV were provided by J. Butler, FIRS database, SeaCLEF 2016 dataset, and Kaggle fish database. The different techniques classification accuracies are from 69.57% to 100% and it is also demonstrated in Fig. 2. The field of major contribution in table 4 shows the most important work included in the FC papers and the field of advantage includes the FC techniques benefits.

The number of extracted features is demonstrated in Fig. 3. The x-axis shows the name of authors of the FC techniques. The y-axis shows the number of the extracted features in the survey papers. The extracted features calculation is based on the number of the extracted features in FC papers. If the number of the extracted features is not reported in the survey papers then it is denoted as 0.

The authors in (Alsmadi et al., 2012, 2011; Badawi and Alsmadi, 2014; Kutlu et al., 2017) observed that increasing the number of extracted features effectively improves the classification accuracy. From Tables 1, 2, And 4; it's clearly understood that the combination of the mean imputation preprocessing method, feature extraction method FSS algorithms, and SVM method offers a higher FC accuracy result (100%) using 20 fish species which contains 1516 images. Compared to other FC methods, SVM classification is the most commonly employed classifier (SVM was used 4 times to classify fish) which classifies the fish species images. From Tables 2 And 4, the GIS on Fishes, F4K, and knowledge databases are commonly used in a lot of papers. Also, the self-collected dataset is employed with the SVM and provided 95.92% accuracy.

As can be observed from the above-reported survey papers, the number is very limited as opposed to other conventional applications of classification. Accordingly, Alsmadi et al. (Al Smadi, 2016; Alsmadi et al., 2012) reported several studies on fish image classification problems, whereby the majority of PR-based studies were focusing on resolving and/or improving the traditional recognition applications. These include the studies on face recognition (Alsmadi, 2016), land cover classification, fingerprint identification, eye print identification (Thalji and Alsmadi, 2013), medical image segmentation (Alsmadi, 2018), Content-Based Image Retrieval (CBIR) (Alsmadi, 2020, 2017) as well as handwriting recognition. Conversely, the majority of studies on fish image classification focusing on non-poisonous fish grounded on shape analysis have disregarded the poison fish. Hence, people die in real life due to the failure to discriminate between the poisonous fish and non-poisonous counterparts (Al Smadi, 2016; Alsmadi et al., 2012, 2010).

5. Future research directions

This section offers several scientific problems that haven't been addressed in prior FC research. Also, significant work is essential to improve the efficiency of various FC techniques. The challenges that are essential to be addressed are below.

Table 4
Performance analysis of FC techniques.

Author name	FC algorithm name	Database name	Classification accuracy (%)	Major contribution	Advantages
Kaya et al. (2018)	ANN	F4K	98.88	Extraction of shape, texture and color features	Performed a generic FC with high accuracy
Lee et al. (2003)	MDC	Self-collected	90	Detection of fish landmark points and contour features	More efficient for finding the essential landmark points
Lee et al. (2008)	TADA	Self-collected	73.3	Finding critical landmark points on the fish contour using CF analysis	More efficient for finding the essential landmark points
Mokti and Salam (2008)	Not specified	Not reported	x	Improve result in terms of region grouping and obtained clearer boundaries of segmented regions.	Improved the contour extraction for further processing
Nery et al. (2005)	Bayesian classifier	CNPq-Brazil	81	Propose a general set of features and their correspondent weights that can be used as a priori information by the classifier	Determinate of which input information must bring robust fish discrimination.
Hossain et al. (2016)	SVM	CLEF 2015	91.7	detection fish in low-quality underwater video	Better accuracy for detecting and identifying fishes
Alsmadi et al. (2010)	BP algorithm	GIS on Fishes	86	Extraction of size and shape measurements	Wealthy capability for size and shape analysis
Alsmadi et al. (2010)	BP algorithm	GIS on Fishes	84	Extraction of color texture information	Wealthy capability for Color texture analysis
Alsmadi et al. (2011)	BP algorithm	GIS on Fishes	84	Extraction of statistical features standard deviation, homogeneity, and energy	A reliable method for FC based on color signature
Badawi and Alsmadi (2014)	GAILS-BPC	GIS on Fishes	85	Extraction of anchor points, texture, and statistical features	Performed a generic FC with high accuracy
Alsmadi et al. (2011)	HGAGD-BPC	GIS on Fishes	96	Extraction of Potential Local Geometric Features (PLGF) and shape measurements	Robust features & achieve good results
Hnin and Lynn (2016)	SVM	Mandalay University	100	automated taxonomic identification of the species using a morphometric variation among fish species	Identified taxonomic characters of fish species based on specimens
İşçiMEN et al. (2014)	Naive Bayesian classifier	Self-collected	93.10	Extraction of color, and statistical texture features	Robust features & achieve good results
Hu et al. (2012)	multiclass SVM	Self-collected	95.92	Extraction of statistical texture features, and wavelet-based texture features in different color space	Wavelet domain feature extractor with Bior4.4 wavelet filter in HSV color space is the best features for fish species
Ogunlana et al. (2015)	SVM	Self-collected	78.59	Extraction of shape features	Reliable and adequate method for FC
Daramola and Omololu, (2016)	BP algorithm	Self-collected	94	Classified fish images into distinct classes based on their physical form	An accurate system capable of classifying fish images
Qin et al. (2016)	linear SVM classifier	F4K database	98.57	Find a solution to accurate underwater object recognition.	Robust features & achieve good results
Kratzert and Mader (2018)	CNN	Self-collected from Austrian rivers	93.3	An approach for fish species classification in video-based monitoring	Achieve good results
Freitas et al. (2013)	SVM, KNN, DT	AQUARIO28E40I dataset	92.3	Extraction of color information	An accurate system capable of classifying fish images
Mushfieldt et al. (2012)	SVM	knowledge database	88.5	Segmentation of fish image to obtain shape and color representation	Achieve good results
Chuang et al. (2016)	Hierarchical partial classifier algorithm	F4K dataset	93.8	Propose a framework that consists of a fully unsupervised feature learning technique and an error-resilient classifier.	Achieves high accuracy on both public and self-collected underwater fish images
Matai et al. (2010)	PCA algorithm	Self-collected	100	PCA for FC	Reliable algorithm for FC
Saitoh et al. (2016)	RF	Self-collected	87.3	Propose a fish image recognition method using feature points (Geometric, Bags of visual words model and texture features) for fish images with complicated backgrounds	Wealthy capability for Geometric, Bags of visual words model and texture analysis
Miyazono and Saitoh (2018)	CNN	Self-collected through the Web	91.4	Propose a novel feature-points representation method named annotated image, and propose a fish species recognition method based on CNN	Effective recognition performance
Pornpanomchai et al. (2013)	ANN	FIRS database	81.67	Extraction of shape, texture and color information	Reliable algorithm for FC
Jäger et al. (2016)	multiclass SVM	SeaCLEF 2016 dataset	66	Apply CNNs for object detection as well as fish species classification	Effective for fish object detection
Fouad et al. (2013)	ANN classifier SVM algorithm	Self- collected	69,57 94.44	Introduces an automatic classification approach for the Nile Tilapia fish using SVMs algorithm in conjunction with feature extraction techniques based on SIFT and SURF algorithms.	Effective classification performance
Al Smadi (2016)	GAGD-BPC	GIS on Fishes	83.2	Extraction of anchor points, texture, and statistical features	Performed a generic FC with high accuracy

Table 4 (*continued*)

Author name	FC algorithm name	Database name	Classification accuracy (%)	Major contribution	Advantages
Ali-Gombe et al. (2017)	Deep CNN	Kaggle fish database	97.20	Analyzed the performance of deep CNNs on noisy images of fish species	High accuracy and effective FC based on the noisy image
Sayed et al. (2018)	SVM and DT	adopted fish dataset	96	Proposed an automated fish species identification system based on a modified CSA.	Flexible feature selection and high FC accuracy
Kutlu et al. (2017)	Nearest Neighbour algorithm	Self-collected	99	Finding critical landmark points on the fish contour and Extraction shape measurements using distance measurements	Wealthy capability for size and shape analysis
Hernández-Serna and Jiménez-Segura (2014)	Neural Network	Self-collected	91.65	Extraction of geometrical, and texture and morphological features	Does not depend on variations
Kartika and Herumurti, 2016)	SVM and Naive Bayes algorithm	Self-collected	94	Extraction of RGB to HSV color features	Robust features and achieve good results
Chen et al. (2017)	CNNs	NCFM dataset	70	Extraction of context information features	Handle the variation of pose and scale of fish and extract discriminative features to distinguish fish
Andayani et al. (2019)	Probabilistic Neural Network	Self-collected	89.65	Extraction of geometric invariant moment feature, GLCM texture feature and color feature	Classify fish species effectively and efficiently
Alsmadi et al. (2019)	MA-B Classifier	GIS on Fishes	90	Extraction of anchor points, texture, and statistical features	Performed a generic FC with high accuracy
Alsmadi (2019)	GTB Classifier	GIS on Fishes	87	Extraction of anchor points, color texture, and color features	Robust features and achieve good results
Islam et al. (2019)	SVM	BDIndigenousFish2019	90	It can extract different types of features using two different binary patterns	Effective classification performance
Chhabra et al. (2020)	Stacking ensemble model	Self-collected	93.8	It can easily detect simple features like edges, simple shapes	High accuracy and effective FC based on the noisy image
Taheri-Garavand et al. (2020)	deep CNN	Self-collected	98.21	It can automatically extract features directly from images	Overcoming the complexity and difficulties of the traditional methods
Yusup et al. (2020)	YOLO Deep Learning algorithm	Self-collected	82.82	It can identify the fish object automatically	Faster object detection
Rekha et al. (2019)	CNN	Self-collected	92	CNN, with different architectures, was used at the detection and classification step for features extraction and analysis	Effective recognition performance
dos Santos and Gonçalves (2019)	CNN	AQUARIO28E40I dataset	96	Improving the classification of fish species with similar characteristics	Effective recognition performance

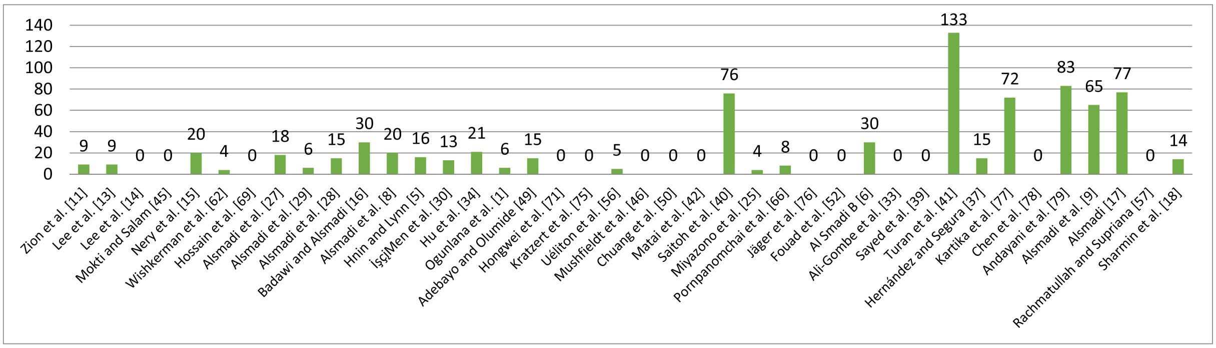

Fig. 3. Number of extracted features.

DL typically has attained promising results in the pattern recognition field, but the DL models' context is not fully recognized and is considered to be a black box. For instance, numerous researchers modified the well-known DL algorithms, like CNN or Deep NN, for improving classification efficiency (Rawat and Wang, 2017; Pak and Kim, 2017; Yang et al., 2018). Also, it is challenging to discover the optimal values and correct configuration for the node numbers and layer numbers in various layers. The information of the basic domain is necessary also for choosing values for the epoch's number, rate of learning, and the regularizer strength. Thus; in the future, approaches for automatic optimization can be introduced for determining optimum values for various elements of DL architecture for specific datasets for FC and other datasets for pattern recognition.

Moreover, investigating several aspects of recurrent neural networks and deep neural networks for learning the fish shape to evaluate and design effective solutions is necessary. A method relying on combining hand-craft features and deep features extracted by CNN (Hassaballah and Awad, 2016) as well as integrating the global shape constraints into the architecture of CNN to entirely utilize the deep model's power would be of concern research direction. Furthermore, multi-task learning using fusing intermediate layers and CNNs from CNN to bring both semantically and geometry rich features together may produce an enhanced performance of detection.

CNN-based models provide a high classification accuracy even with the usual limitations of translation, rotation, overlapping, amongst others. But, having to try to collect and correct large amounts of sample images manually for training remains a strong limitation. Thus, methods that depend on artificial training data are proposed. Some rely on the data augmentation concept using the existing data samples and application of affine transformations for increasing the number of available samples for each class. Furthermore, transfer learning was considered for addressing this matter, as it reproduces a model success on a similar task. Recently Ali-Gombe et al. (Ali-Gombe et al., 2017) introduced a comparative study of transfer learning and data augmentation on the FC context, they concluded that data manual annotation was a fundamental requirement for increasing rates of accuracy for these options.

Typically, DL algorithms require a large amount of training data. When the range of training is limited, it won't produce precise enough results (Ha et al., 2018; Doreswamy and Santosh, 2018). Moreover, the DL algorithm's efficiency will be improved on massive fish datasets. There are two methods to solve this issue. By utilizing low learning algorithms for capturing training data, or by using a variety of enhancing approaches, including color casting, rotating, and cropping. Additional investigations are essential for producing more detailed training data, such that training the DL design with more distinguishing features and reliability.

Adding preprocessing methods which are specifically designed before feature extraction can efficiently enhance the FC system performance in sever variations case as well as improving methods that use color information as an alternative of grey images.

Like other domains, FC benefited from the integration of multiple sources of information. The sources of information may include fish texture analysis, the shape of various shape parts, color signature, distances ratios in the fish object, etc. this may help in robust feature extraction and reaching improved classification results.

More comparative studies can be performed with other DL architectures for fish image detection and classification on multiple fish images and particularly video datasets obtained in the unlimited underwater environment. It could be of interest to investigate the improvement of performance by involving the color signature information in DL architecture training such as CNN. More work needs to be investigated on the underwater fish species faced by water turbidity, background confusion, and environmental challenges. Underwater fish species' real-time monitoring can be further enhanced to improve classification performance.

6. Conclusion

This survey paper provided a comprehensive review of datasets, preprocessing techniques, feature extraction methods, and classification algorithms for the FC domain. In the preprocessing stage, several methods were reviewed such as anchor points detection, ROI extraction, and image enhancement. In addition, the conventional feature extraction methods were classified into five groups (shape feature-based methods, local and global feature-based methods, color feature-based methods, texture feature-based methods, and the combination-based feature extraction methods). The performance of the previous FC works is compared relying on the used datasets, number of fish images, number of fish species/-families, number of extracted features, major contributions, and classification accuracy. Moreover; the advantages of algorithms are elaborated and discussed to achieve this survey goal. For efficient performance, the most used dataset is the GIS on Fishes, F4K, and knowledge database. Fish image resizing, fish detection, landmark/anchor points and image cropping methods are mostly utilized in the preprocessing step. For feature extraction; distance and angle measurements, GLCM, Gabor filter, SIFT, and SURF are most commonly used. For classification; the most commonly used algorithms are SVM, BP algorithm, HGAGD-BPC, GAILS-BPC, Bayesian classifier, and CNN. In conclusion, the authors expect this work to be beneficial for the industrial field, agriculture domain, and marine scientists, and a useful starting point for new FC approaches, and a common ground for a wide range of benefits in the area of FC.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Please cite this article as: M. K. Alsmadi and I. Almarashdeh, A survey on fish classification techniques, Journal of King Saud University – Computer and Information Sciences, https://doi.org/10.1016/j.jksuci.2020.07.005