Journal of Ecohumanism
2024
Volume: 3, No: 4, pp. 2529 – 2555
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i4.3773

Overall Study in Image Classification Techniques

Saja Hikmat Dawood[1]

Abstract

The era in which we live has become the era of big data, particularly with the spread of the concept of Internet-of-Things (IoT) and artificial-intelligence (AI). Images constitute a large portion of this data that is created and handled. Image classification is the process of identifying and labeling groups of pixels or vectors inside an image using certain criteria. Major image classification techniques divided into two categories which are supervised and unsupervised techniques. This study looks at various research, techniques, and issues of image classification. The focus is on summarizing the main advanced classification strategies and methods such as (K-Mean clustering, Fuzzy measure, Artificial Neural Networks (ANN), Decision-Tree (DT), Support-Vector-Machines (SVMs), Naive Bayes (NB), K-Nearest-Neighbor (KNN), Random-Forest (RF), etc.) that can be utilized after some update to enhance classification accuracy. Also, this study shows the common challenges and solutions in this area.

Keywords: *Image Classification, Artificial Neural Networks (ANN), Conventional Machine Learning Techniques, Deep neural networks (DNNs) Techniques.*

Introduction

Although classifying objects is a simple process for human eyes and brains [1], machines find it difficult to do so. In computer vision, image classification is a crucial process. It is the process of grouping images according to predefined categories that correspond to their visual content. A significant aspect of machine learning is classification of images [2].

Pre-processing, object detection, segmentation, feature extraction and classification are all included in the image classification process. The Image Classification system is consisting of a database containing pre-set patterns that are used to identify which category an object belongs to. In many application fields, such as industrial visual inspection, robotic navigation, biomedical imaging, video surveillance, biometry, remote sensing, and vehicle navigation, etc. image classification is an essential and difficult problem. The phases in the classification approaches are shown in Fig. 1 [3]

The core objective of image classification is the precise identification of the characteristics that are present in an image. Both supervised and unsupervised classifications are used in image classification. in supervised classification, both human involvement and a trained database are employed. Since unsupervised classification is entirely computer-operated, no human involvement is necessary at all [4].

The supervised classification techniques which is also known as conventional machine-learning techniques like: support-vector-machine (SVM), Random-Forest, K-Nearest-Neighbour (KNN) Classifiers [2].

While the unsupervised classification which is also known as a deep-neural-network like: Convolutional-neural-network (CNN); it is also known as ConvNets [5].

This study aims to provide light on the state of art in image classification techniques generally, highlighting their significance, range of applications, and developing techniques. It aims to contribute to the greater knowledge and development of image classification systems across multiple domains by clarifying the principles and recent developments in this subject.

[1] Department of Computer Science, Collage of Basic Education, University of Mustansiriyah, Baghdad, Iraq, Email: saja2018ss@uomustansiriyah.edu.iq.

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The paper is structure as follows: Section II, discusses the main phases involved in image processing and image classification. Section III, explain the different image classification techniques and give a literature review for these techniques. Section IV, the Performance Metrics that was utilized for Evaluation of classification techniques. In section V, some of the common Challenges and proposed solutions for these challenges. finally.

section VI, provides the conclusion from the related works.

Main Phases Involved in Image Processing and Image Classification

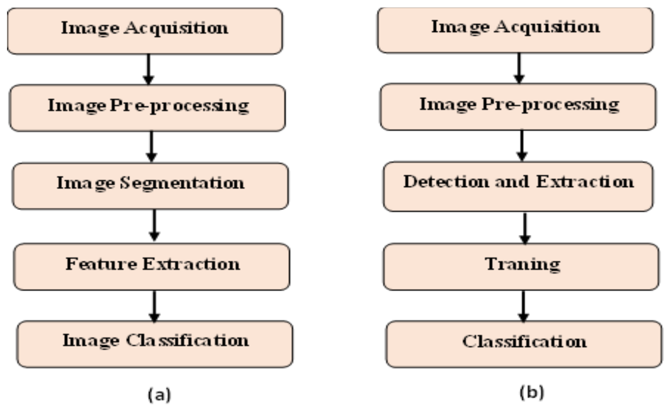

Figure 1: (a) Main phases in image processing [6], (b) Main steps in image classification [3]

As shown in figure 1(a). image processing includes the following phases:

Image Acquisition

It is the initial step that is carried. The difficulty of retrieving a digital image from a physical source is a crude demonstration of this. Digital cameras or other comparable devices are utilized to capture the images used in the processes mentioned [6]. Each strategy proves more appropriate in certain situations and less so in others, based on the associated benefits and drawbacks [7].

Pre-processing

The practice of improving captured image quality by altering its input image's features and handling with unwanted artifacts is known as image pre-processing. Image enhancement or Image restoration are the terms used to describe this phase. Noise and blurring reduction, converting RGB images to greyscale or HIS images, and other processes are done to improve the quality of the input image. This stage plays a crucial role and affects the classification process as a whole [6] [7].

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Image Segmentation

Image segmentation is part of picture analysis process, that divides the digital picture into many parts and extracting relevant areas (also called areas of interest) for additional analysis [6].

There are different techniques for image segmentation such as: -

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Region based segmentation

This method combines regions growing, clustering, splitting and merging.

- Region Growing include grouping images into sub-regions, but this technique has noise sensitivity and computationally intensive.
- Region Splitting and Merging include partition images into sub-regions, then each sub-region undergoes a merging and/or splitting process in accordance with predetermined segmentation criteria, but this technique is sophisticated and highly compositional.
- These techniques are not appropriate for pictures with shadows or shading and require more complicated computing [8].

Threshold Based Segmentation

This method divides an image into subregions based on variations in gray scale values and can extract foreground objects from the background. It converts gray-level images into binary images, reducing the complexity of data and simplifying recognition. However, it is noise- sensitive, lacks spatial information, and increases computational complexity with larger images. Otsu technique use this method [8].

Edge Based Segmentation

This method involves locating the image's edges on its gradient in order to determine the objects' boundaries. This method uses first order-derivative/gradient operators, second-derivative operators, and optimal-edge detectors.

- First order derivative detects edges when intensity level discontinuity occurs. Edges can be identified using Roberts, Sobel and Prewitt operators that calculate the magnitude of the first derivative.
- Second derivative operators detect edges whenever the lighter side becomes negative and the darker side becomes positive. It is very susceptible to noise. Laplacian operator and the Difference of Gaussian (DoG) are second derivative operators, which looks for zero-crossings to locate edges.
- The optimal edge detector generates noise-resistant, continuous edges. Strong and weak edges can also be detected by it. Canny edge detector is the optimal one.

The edge-based segmentation is weak due to missing and disjointed edges, noise sensitivity, and sensitivity to expanding edges between important regions [8].

Clustering

Clustering is a method of organizing data into groups called clusters, with each cluster containing data more similar to others. Clusters are formed based on a number of attributes, such as size, color and texture. clusters can found in two types: hierarchical and partition. Such examples for this method are [8]:-

- K-mean Clustering

The K-means method is used to group picture pixels according to similarity characteristics such as color, distance, and intensity. Clustering allows big data points to be quickly, easily, and efficiently grouped. Its drawbacks include noise sensitivity, a restricted number of cluster selections, and inconsistent results resulting from varying starting centroids and more shows in [8].

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- Fuzzy Clustering/ Fuzzy C-Means (FCM)

This technique is also known as soft clustering, it allows each data point to be a part of several clusters [9].

Artificial Neural Network (ANN)

ANN is a learning strategy used in decision making, particularly in medical images segmentation. It's employed to distinguish a given image from its backdrop, with connected nodes having specific weights [9].

There are also other methods for the segmentation process, but the common methods for segmentation were reviewed above

Feature Extraction

Features are characteristics of an object in an image that distinguish it from others. Feature extraction is crucial for entity recognition, as they describe the object. Data structures are used to represent the object's extracted characteristics. Examples of characteristics include color, morphology, edges, and texture, which can be useful in detection.

In order to generate a meaningful data structure, the grey level co-occurrence matrix approach uses pixel values as indexes to construct a matrix. It then looks for repeated pixel values and matches them with index values [6].

Image Classification

Classification identifies unknown objects by comparing them with recorded patterns, If the comparison is successful, the unidentified object is found [6].

Image classification includes the following steps as shown in figure 1 (b):

- The first and second steps (Image Acquisition and Pre-processing) are as shown above in image processing section.

- Detection and extraction: - object detection involves perceiving the location and other characteristics of an object. while features extraction, an approximation of the object's path in the picture plane is obtained from the detected object.

- Training: - choosing the exacting quality that portrayed the pattern properly [10].

Image Classification Techniques and Literature Review

One of the crucial and intricate steps in image processing is image classification. There are several techniques for classifying images as shown in Figure 2. Supervised-and-unsupervised-classification are the two primary techniques for classifying images.

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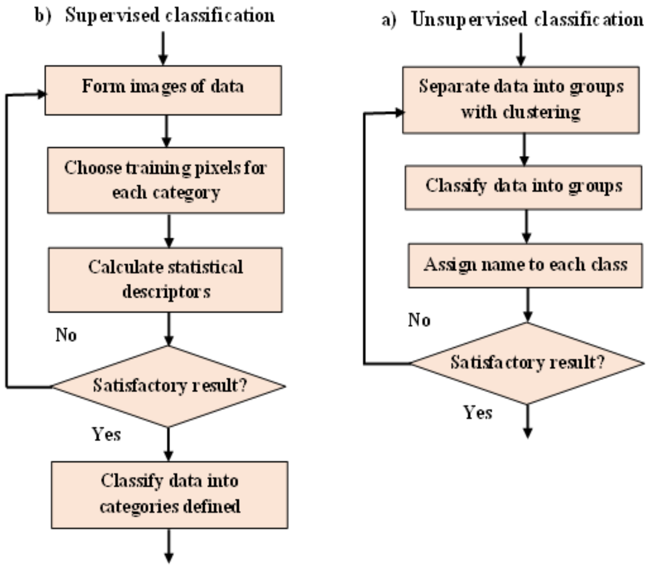

Figure 2. Supervised and Unsupervised Classification [10]

Supervised-Classification

Certain pixels are thought to be grouped & provide the class labels in supervised classification. We refer to this procedure as training. Subsequently, the classifier use trained pixels to categorize more pictures. Before the testing procedure can begin, some information must be gathered by the analyst. For every informative class, the analyst finds sample training sites in this way, and the program also creates decision limits. Maximum likelihood, minimal distance to mean, and parallelepiped are popular supervised classification techniques. In supervised categorization, the following stages are involved:

- Each informative class's training areas are determined by the analyst.
- Signatures indicate (covariance, variance, mean, etc.)
- Every pixel has a classification.
- Map Informational Class [3].

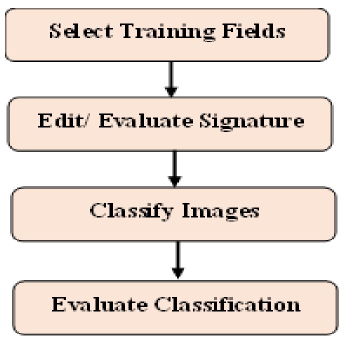

Figure 3: Steps In Supervised Classification [10]

Unsupervised Classification

Pixels are grouped using their attributes in an unsupervised manner. Groups are referred to as clusters and this process is called clustering. The user chooses how many clusters he wants in this case. Whenever there are no training pixels available, the unsupervised classification method is employed. The process of

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unsupervised categorization does not require prior knowledge. It is entirely automated, therefore no human annotation is needed. This method both finds and labels data clusters for analysts. Unsupervised classification involves the following steps:

- Clustering data
- Classifying all pixels based on clusters.
- Spectral classes Map.
- Analysts labeled the clusters.
- Map informative class [3]

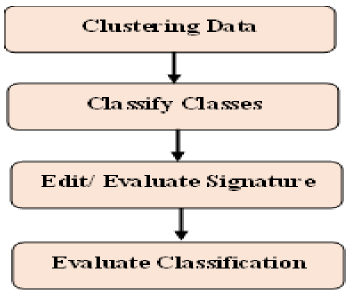

Figure 4: Steps in Unsupervised Classification [10]

Below is illustration of different methods that have been used in image classification: -

K-means Clustering

It is type of Unsupervised Classification. The steps involve in this algorithm are: -

Step 1: - starts by computing the number of clusters (k).

Step 2: - suppose the cluster center (centroid). Any object/ item at step random can serve as the first centroid.

Step 3: - repeat the three phases listed below until this method reach convergence (a steady state).

- Find the coordinates of the centroids.
- Calculate the distance between each item and the centroids.
- group the items according to the shortest distance [11].

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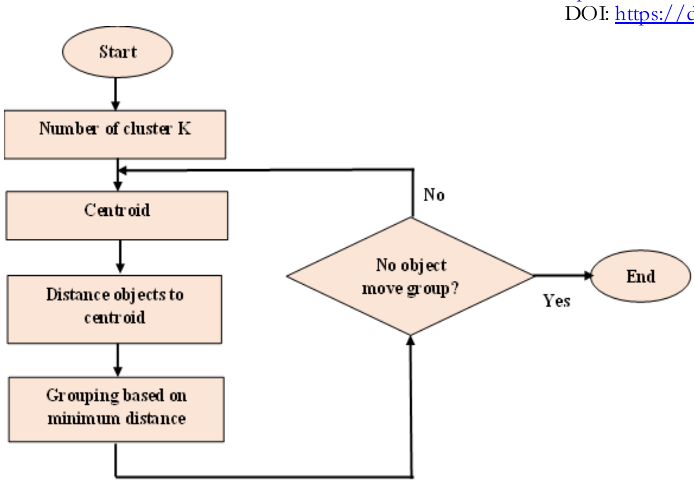

Figure 5: K-mean algorithm [11]

Fuzzy Measure

Different stochastic connections are found in fuzzy classification to characterize an image's attributes. The several forms of stochastic are combined to provide a collection of qualities, some of which are fuzzy in nature. It offers the chance to give comparable descriptions of several kinds of stochastic features. The fuzzy integral and threshold choices determine performance and accuracy [3].

Artificial Neural Network (ANN)

ANN is a kind of artificial-intelligence which uses a series of layers, each with a collection of neurons connected via weighted interconnections, to store experience knowledge. each artificial neuron produces an outcome using a specific activation-function like (Gaussian, piecewise-sigmoid, linear, etc.), after computing the weighted total of its incoming signals. The general structure of artificial neuron is illustrated in (Figure 6). The amount of nodes in input layer equals to the dimensions of every pixel, while number of nodes in output layer equals to the amount of classes information.

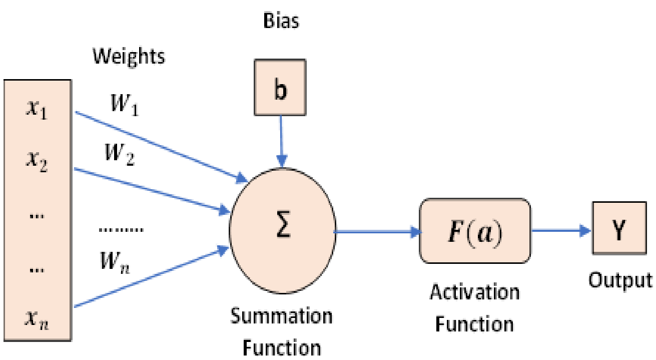

Figure 6: General Structure of Artificial Neuron [12]

There are basically three categorize of ANN as shown in (Figure 7) and the different types under each category.

The 1st one is feed-forward-neural-network (FFNN) with back propagation learning which are frequently employed to adjust connection weights from training data using the error difference that exists between the intended and the produced output. training process is completed when the error is lower than a certain threshold. The classifier then employed to perfrom the classification after receiving all of the testing data

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[3]. FFNN is simple network with a forward-oriented connection pattern, allowing data to flow from input to hidden layers and output. There are no loops in the data flow's pathways.

The 2nd one is recurrent neural network (RNNs) allow loops inside the cells provide feedback on computation failures by referencing the target values. The weights of the related inputs are updated with the assistance of error feedback [13].

The 3rd one is Deep-neural-networks (DNNs) are the process of employing a neural-network that has been trained on enormous quantities of data to categorize, cluster, and predict objects. Such as convolutional networks that extract features from large amounts of data, such as patterns, textures, edges, and brightness, which are reusable for various image processing scenarios The deep learning approach merges feature extraction and classification onto a single network, unlike to conventional image classification technique [14].

DNN can also classified into supervised and unsupervised.

The supervised deep neural network examples are: generative-adversarial-network (GAN), long-short-term-memory (LSTM), recurrent-neural-networks (RNNs), gated-recurrent-unit (GRU), convolutional-neural-networks (CNNs), etc.

The unsupervised deep neural network examples are: Deep Transfer Network (DTN), autoencoders (AE), Tensor Deep Stack Networks (TDSN), deep belief networks (DBN), etc [14].

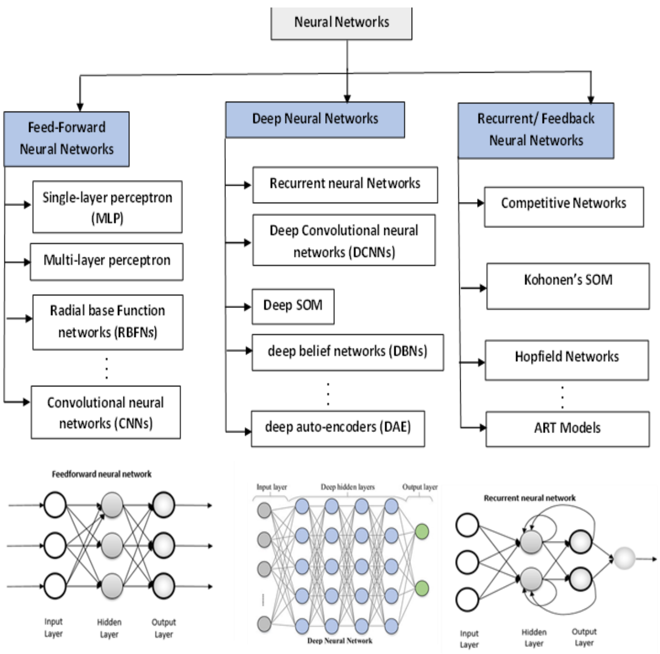

Figure 7: ANN Categorization [13] [15]

Support-Vector-Machine (SVM)

SVM is a supervised-learning method. Its implicitly translate incoming feature vectors to space of higher-dimensional using Gaussian width and kernel function [3]. Three primary kernel functions may be utilized with SVMs: polynomial, RBF, and linear [16].

As shown in (Figure 8), SVM is built upon a process that divides / classifies two classes: class-A & class-B. With a maximum width (margin), the ideal hyper-plane (separator) attempts to divide the two classes; Two

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parallel-hyper-planes are formed in a symmetric on each side of hyper-plane which splits the data, taking use of margin between the two external-hyper-planes.

By minimizing the upper bound of the generalization error, SVMs seek to reduce the structural risk reducing attitude. SVM method attempts to identify a decision function which minimizes functional. They make it possible to use a small training set to train nonlinear classifiers in high-dimensional regions. Selecting a vector division, also known as the support vectors, that establishes the proper borders between the classes fit makes this feasible [3].

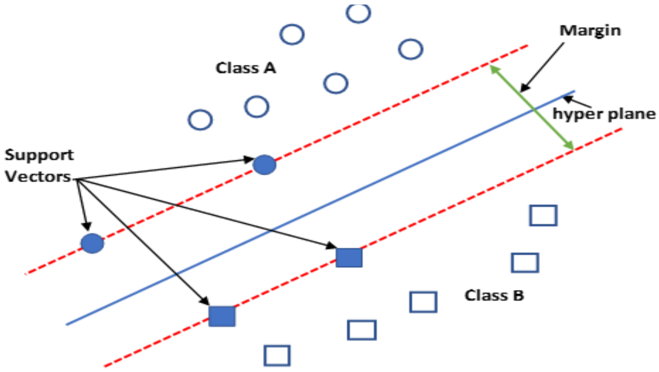

Figure 8: SVM Dividing Class A And Class B [10]

Decision-Tree (DT)

DT is a supervised-learning method. There are different types of decision tree such as (Decision Tree Classifiers, Pruning Decision Tree, Tree Boosting).

Decision tree classifiers are a non-parametric, hierarchical method used to classify data using a general set of features in a single decision step. They are increasingly important due to their simplicity, computational effectiveness, and ability to automatically choose features, providing easily interpretable information about classification's prognostic ability. The method involves dividing dataset into homogeneous groups and assigning class labels. Three steps make up this method: nodes dividing, locating terminal-nodes and assigning them a class label [3]. Figure 9. Showing how the root node which holds all of the data divided into split nodes and leaf nodes based on specific threshold (T) that specified according to the nature of the problem [10].

Pruning the decision tree and tree boosting can decrease classification mistakes when dealing with data that is not part of the training set. Pruning removes complex parts of the tree, while tree boosting iteratively generates multiple classifiers, reducing errors in weak learning algorithms. Decision tree classifiers offer an efficient classification approach [10].

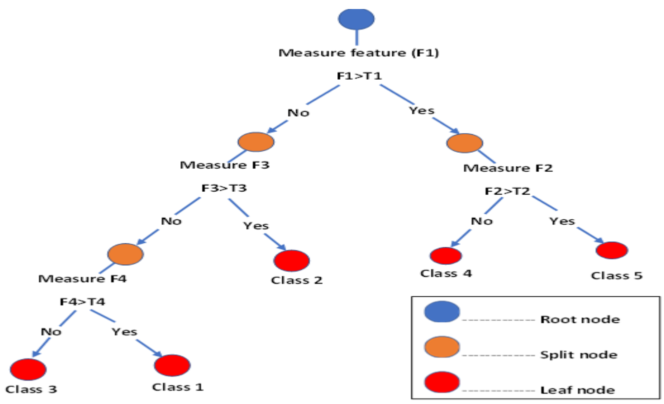

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Figure 9: Decision tree classifier [10]

Naive Bayes (NB)

Naive Bayes is a supervised-learning classifier constructed using Bayes theorem [17], assigning the class with the largest predicted probability to the feature vector. which is based on a probability representation. It requires a limited dataset for training, Also, it is easy of use and enables good performance, resistant to outliers, and has flexible decision boundaries, which prevents overtraining. However, it has poor performance for complex multiclass configurations [3].

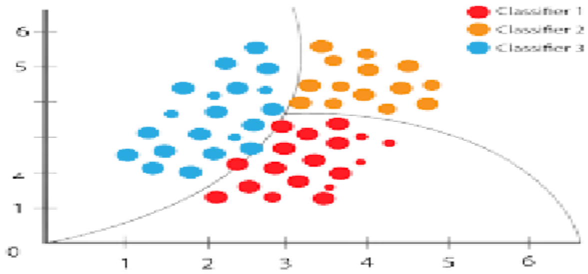

Figure 10: Naive Bayes classifier [18]

K-Nearest-Neighbor (KNN)

Among the most well-liked supervised machine-learning-techniques is the k-nearest neighbors (KNN) algorithm. In order to forecast the new data points values, it employs "feature similarity," classifying them according to how closely they resemble the training set [17].

Figure 10. show how the K value have the influence in determining the class of the new data [19].

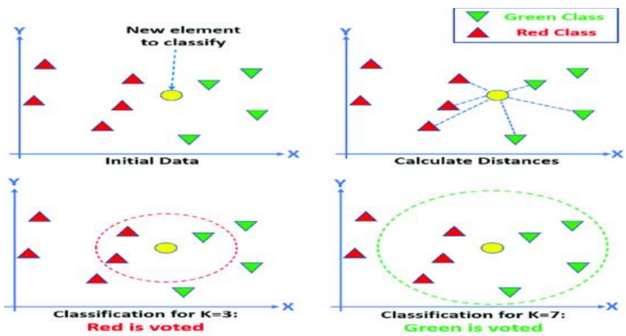

Figure 11: K-Nearest Neighbor [19]

Random Forest (RF)

RF is a supervised machine-learning-technique which generates many decision trees and aggregates them to get forecasts that are more precise and consistent. This approach yields consistently high-quality outcomes and is both versatile and easy to utilize. one of its main advantages is its effectiveness in solving regression and classification tasks [20].

This method's primary drawback is its computational complexity and poor performance when dealing with an extensive amount of trees, which makes it unsuitable for real-time operations [21].

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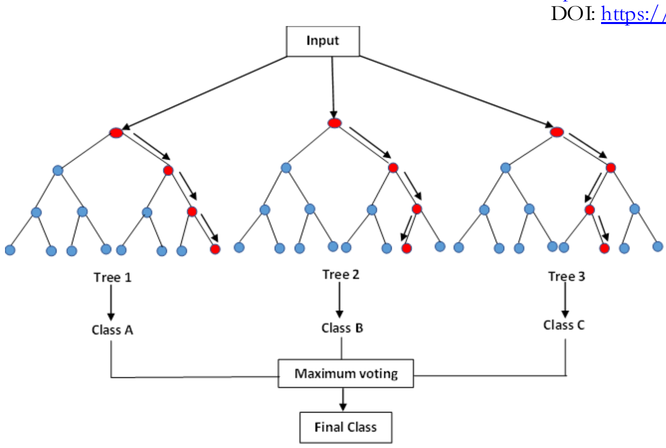

Figure 12: Random Forest [20]

Bagged Tree

A meta-algorithm called bagging is used to machine-learning-algorithms for statistical regression and classification to improve their accuracy and stability. By lowering the amount of observations, it reduces variance and guards against overfitting. Bagging allows categorization using several techniques while reducing the quantity of the data. the process involves Using a resampling technique called bootstrapping, samples are repeatedly taken from the original data and replaced. Then, each sample is trained in parallel using different methods, such SVM or Decision Trees. The average of each output is used to determine the aggregated output [22].

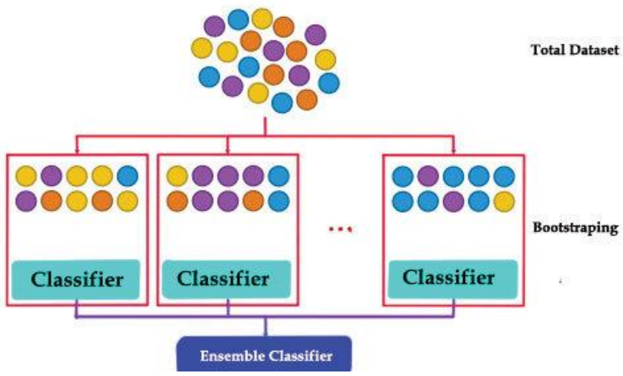

Figure 13: Bagged Tree

Logistic Regression (LR)

Methods for determining the relationship between a collection of predictor variables and a categorical response variable are implied by logistic regression. A function of means, which is a probability, is shown via logistic regression as a function of the exploratory variables. The legitimate transformation is involved in logistic regression [10].

Expectation Maximization (EM) Algorithm

EM is a repetitive process that fits finite mixture models to observable data. It approaches a local maximum in the marginal a posteriori probability function. EM is used to estimate features from missing or partial data sets; however, it is computationally costly. EM methods can be implemented using either multivariate or univariate normal distributions. Univariate EM employs a histogram, whereas multivariate EM employs randomizes and a 3D space vector starting parameters.

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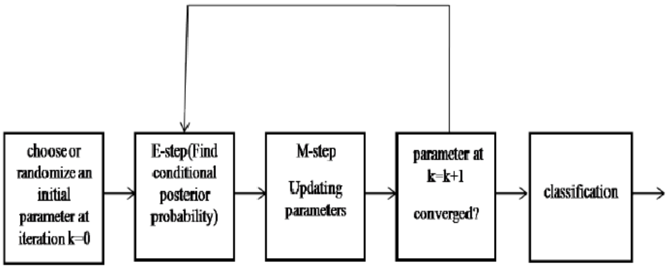

Figure 13: EM Algorithm [11]

The EM algorithm applying two steps:

E-step (expectation): - calculates the conditional posteriori probability.

M-step (maximization): - updated the parameter estimation.

then estimate mean, covariance, and a priori probability for each cluster until convergence is attained [11].

Bayesian Classifier/ Maximum Likelihood

It uses probability theory to the categorization problem. A statistical decision rule assigns pixels to classes based on their probability function. The equation for Bayesian classifiers/ maximum likelihood is shown in ref [11].

Find the probability for each pixel in each class. Pixels are given to class with highest likelihood, and classification is conducted accordingly [11].

Different Image Classification Techniques are shown in TABLE 1.

TABLE 1. A Survey of Different Techniques with their Strengths and Weaknesses

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Ref	year	Technique\ Methodology	Domain\ Data set	pros	Cons	Performance Measurement tools	Future work
[11]	2011	Neural Network (NN), K-means algorithm, EM (univariate and multivariate distribution) algorithm, Maximum likelihood classifier	Two images (2. Simple digital image, 1.SAR image)	- K-means has the shortest time of 1.82sec. - Maximum likelihood classifiers and NN offer better accuracy and are useful for multiple databases. but NN has the highest accuracy of all methods.	- EM (univariate normal distribution) has the worst accuracy. -NN has the longest time. - lacks to other evaluation metrics. - Using limited data for evaluating. - Doesn't discuss the parameters for each classification technique.	Accuracy, time	-
[27]	2011	Independent-Component-Discriminant-Analysis (ICDA)	Four hyperspectral datasets (AVIRIS- Indian-pine, AVIRIS-Hekla, ROSIS, HYDICE-Washington)	- The suggested approach (ICDA) outperformed support vector machines (SVMs). - ICDA Effective with high dimensional data and limited training samples. - ICDA Computationally efficient for large training sets. - Tested on multiple different datasets.	- ICDA results varies depends on the number of independent components (IC) kept. - ICDA Can have higher standard deviation and computationally demanding with small training sets. - Does not naturally use spatial information.	Accuracy, processing time	- Integrating spatial information into the ICDA. - Further investigation of ICA algorithms on classification performance.
[28]	2012	Artificial neural network (ANN) & Support vector machine (SVM)	Roman numerals images of (322 matrixes)	- The precision rate of the proposed model is 86%. - Flexible in adjusting	- long Processing time for complex tasks.	Precision	- Optimizing processing time/ training time. - Enhance model

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				parameters for different classification problems. The model Use two parameters. - simple to create and implement for particular classification issues.	- Long training time for large datasets. - when increasing number of classes, the whole model needs to redesign. - Limited dataset. - Lacks of performance comparison with other methods. - Potential overfitting due to small dataset.		scalability to increase the number of classes. - Develop better multi-class relation to improve the precision.
[29]	2013	Euclidean distance and divergence distance for Fuzzy c-Means (FCM)	benchmark Caltech dataset	- Divergence-FCM (D-FCM) achieved higher classification accuracy (73.33%) compared to standard-FCM (44.61%) and SOM (42.22%). - D-FCM utilize both mean and variance information from image blocks, while standard FCM just uses mean information. - Comparative analysis with conventional algorithms	- The categorization is limited to four categories. - Confusion between motorbike and airplane data. - Limited size of dataset Uses only 200 images per category. - lacks of other evaluation metrics	Accuracy	- Improving feature extraction technique to discriminate Motorbike data from airplane data
[30]	2013	SVM	clear cell kidney carcinoma (KIRC) and glioblastoma multiforme (GBM)	- has good classification performance (84% and 81%). - evaluated fully on two large datasets (GBM and KIRC) of 1400 and 2500 samples.	- No comparison with other models. - Lack of implementation information.	accuracy	-

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DOI: https://doi.org/10.62754/joe.v3i4.3773

[31]	2014	Convolutional neural network (CNN)	Interstitial lung disease (ILD) database	- The customized CNN approach yielded best classification results. - addresses overfitting problem by using input distortion and dropout. - Visualization of learned features - Detailed information about implementation.	- Using limited data for evaluating. - CNN generalizability to other medical images or texture classification problems not widely validated.	recall and precision	-
[32]	2015	Rough-Fuzzy Artificial Neural Network (RFANN)	biological image (cut wood images)	- Efficient elimination of features (19/4) with no accuracy loss. - Reduced the computational complexity and runtime by processing 21% only. - Reduced dependence on human specialists. - shown good generalization abilities.	- Limited testing on a small dataset. - Not explored for other applications. - Lack of comparisons with other methods. - requires some expert for generation of inference rules.	Error (Training and Testing error)	- Testing on larger datasets. - Applying RFANN to other classification problems. - Reducing Dependence on Human Experts by only generating membership function.
[10]	2016	ANN, SVM, Decision Tree, and Hybrid method of Refined Gravity Search Algorithm (RGSA) and SVM	brain tumor	- proposed RGSA algorithm show better classification accuracy, while ANN, SVM, and Decision Tree show low accuracy across all datasets.	- it may not extensively address the scalability or generalizability of the Hybrid RGSA and SVM to diverse image datasets or domains.	Accuracy, Classification Rate	-
[33]	2016	fuzzy classifiers and boosting	PASCAL Visual Object Classes (VOC) dataset.	- innovative strategy improves classification accuracy while reducing	- Limited dataset only 3 object classes. - lacks of comparisons	Negative and Positive learning samples, accuracy on testing set,	-

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				learning and testing time by 35 and 32% respectively. - Flexible method that allows adding new object classes by just adding new fuzzy rules.	with other methods.	Learning and Testing time	
[34]	2017	principal component analysis (PCA) + kmeans clustering algorithm + multi-class support-vector-machine (MSVM).	Three benchmark image datasets (Hyperspectral image (HSI))	- (k-means-clustering + PCA + M-SVM) achieves greater time of execution and classification accuracy than typical PCA + M-SVM technique. - performance is validated using both quantitative and visual classification data.	- limited comparison (only one method). - Not examined on datasets that have multiple classes.	Overall and average Accuracy, Execution Time	- Accelerate system performance by using efficient methods for HSI dimensionality reduction and classification. - applying approach on big HSI datasets with several classes.
[1]	2017	Quadratic SVM and Linear SVM. trained and tested using Bag of Words (BoW) and pre-trained CNN (AlexNet)	200 images in 5 groups taken from Caltech 256 dataset	- Both SVM classifiers trained by CNN, shown very high accuracy. But Quadratic SVM slightly outperformed Linear SVM. - CNN extract features better than BoW.	- Limited dataset. - BoW did not perform well with the 10-fold cross-validation approach. Where the accuracy dropped.	Accuracy (ACC)	-
[35]	2018	Convolutional Neural Network (CNN)	MNIST dataset of grayscale images of handwritten digits	- this model achieves great accuracy to 98%.	- demand more processing power. - Doesn't deal with color images - Performance on more complex datasets or real-world images needs further	LOSS, ACC, VAL_LOSS, VAL_ACC	- enhance model accuracy by increasing layers and GPU cluster input for network training. - classifying colored images of larger sizes.

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					validation and generalization.		
[36]	2018	Deep learning	ImageNet database	- The deep learning system's show high classification accuracy even in specific test images.	- lacks of evaluation metrics and comparisons with other methods. - lacks of discussion about parameters and setup.	-	-
[37]	2019	Deep CNN (oriented fast and rotated binary (ORB) + linear SVM, transfer learning with CNNs (VGG16, InceptionV3), and capsule networks)	dataset of chest X-ray images	- using different model of data augmentation and using another dataset (OCT dataset) to enhance performance. - CNN with transfer learning is the most effective of the three approaches. - capsule network is better than SVM+ ORB.	. -Limited size of dataset which limiting the generalizability. - does not extensively compare the performance of capsule networks with other methods.	Accuracy, Specifcity, Recall	- stabilizing the training process. - evaluating other powerful CNN models like ResNetv2. - adding visualization to improve CNN-based systems results.
[7]	2019	SVM with Linear kernel, SVM with RBF kernel (SVM-RBF), Multiple Instance Learning (MIL-RL)	Ph² database	- texture + color features yield better results than color features only. - multiple validation approaches (5-fold, 10-fold, leave-one-out cross-validation). - Using real plain photographs. - Provides extensive performance metrics. - MIL-RL yields higher results; - SVM-RBF is quicker than	- using small dataset. - there is no image pre-processing. - The dataset, methods and metrics used doesn't extensively described and clarified. - the study does not extensively compare with other deep learning algorithms.	Accuracy, sensitivity, correctness, specificity, CPU time and F-score.	- Advanced features and algorithms can enhance efficiency. - apps, BOTs, medical solutions, and instructional games might be created for various demographic classes.

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				linear- SVM and MIL-RL methods.			
[38]	2019	Deep-neural-network (DNN) & Tensorflow framework	3,600 flower images across 5 types	- achieved high accuracy, exceeding 90-100%. - Using of Large dataset of 3670 photos. - Compares various model parameters.	- The study is limited to only 5 types. - Lacks comparability with other classification approaches. - No cross-validation was stated. Computational needs are not stated.	Accuracy	-
[39]	2020	SVM, KNN, Discriminant-Analysis (DA), Random-Forest (RF)	kaggle fruit image detection dataset	- Use real-world fruit images. - Use different performance metrics. - KNN classifier achieved highest accuracy (93%).	- using small dataset which limit the generalizability. - Limited to only three fruit types. - Doesn't provide a comparison with deep learning techniques. - "mixed fruit" images were not well handled.	specificity, accuracy, sensitivity, Negative and Positive Predictive Value (NPV, PPV).	- Improve the proposed technique for real-time performance evaluation through training a network model using more mixed fruit pictures.
[40]	2020	SVM with Gaussian radial basis function (RBF) kernel	DICOM dataset of MRI brain tumor images.	- Achieved High accuracy (94.2% average). Outperforms other existing methods (PNN-and FCM). - Using several performance measures for Evaluation.	- Small dataset (750 samples from 30 images) which limiting the generalizability. - performs Only binary classification (normal vs. abnormal).	precision, recall and processing time	- Incorporating effective segmentation and classification models for real-time healthcare applications. - analyzing tumor volume from MRI images using BioGPS and BraTS datasets.
[41]	2020	SVM and CNN	- Small dataset of 350+ noisy images of 5 different classes which have been	- using different data augmentation techniques for enhancement	- initially small dataset size. - Does not discuss overfitting	F1 score, Accuracy, Precision, Recall	-

			processed to get 3000+ images.	dataset size to 3000+ images. - the accuracy of CNN increased by 93.57% from that of SVM of 82%.	problem with augmented dataset. SVM accuracy drop from 93% to 82% after using data augmentation. - lacks of discussion about tuning CNN hyperparameter.		
[2]	2020	K-Nearest-Neighbour (KNN), Random-Forest (RF) and Multi-Layered-Perceptron (MLP)	Fashion-MNIST Data set	- MLP achieved the greatest accuracy at 89.57%, RF at 89.2%, and KNN at 85.87%. - RF having the least time complexity at 34.89 seconds, KNN at 106.92 seconds, and MLP at 521.78 seconds per 100 epochs.	- Time complexity may not be totally fair. Were MLP run for 100 epochs while other methods are not. - Specific details on hyperparameter tuning and implementation are not extensively covered. - focusing only on classical algorithms, missing other advanced deep learning methods.	Time, accuracy, F1 score, recall, complexity and precision.	- models accuracy may be increased through feeding features extracted from image data. - making a comparison between CNN and MLP model.
[17]	2021	Naïve-Bayes & K-nearest-neighbor	dataset of 10 microscopic blood images (Sickle cell anemia detection)	- best classification accuracy of 98.87% with lowest computational time is achieved with hybrid mix of NICK's thresholding and fuzzy C-means with K-nearest neighbor classifier. - Comparison of multiple segmentation	- Using of small dataset (only 10 images). - The study does not handle overlapping red blood cells with sickle cell anemic blood images. - Computational requirements are not addressed. - Potential for overfitting due to small dataset.	accuracy, sensitivity, specificity and precision	- Handling overlapping cells. - Expanding the dataset to improve generalizability.

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				and classification methods. - Using multiple performance measures for Evaluation.			
[42]	2021	Convolutional-neural-networks (CNNs) vs Deep-Belief-Networks (DBNs)	-	- CNN outperform DBNs in classification accuracy. - emphasizes CNNs' better feature extraction capabilities. - Practical implications for real-world applications.	- Lacks of comprehensive experimental results. - lacks of evaluation metrics. - lacks of discussion about parameters and setup. - Limited information about the datasets utilized.	-	-
[5]	2021	Machine-Learning: - SVM, Naïve Bayes, K-Nearest-Neighbor (KNN), Discriminant-Analysis (DA) and Binary Decision Tree (BDT). deep learning model: - AlexNet	2608 histopathological images for neck and head cancer	- utilize cross-validation for robust results. - utilizing data augmentation techniques. - Evaluates using several performance metrics. - using AlexNet for feature extraction. - SVM, KNN, and DA are the most effective techniques. SVM and KNN achieved higher accuracy rate of 99.98%. while DA, BDT and NB achieved 99.81%, 97.32% and 93.68%.	- specific dataset restrict generalizability to other tasks. - Study doesn't focuses on other deep learning models. - Sole reliance on cross-validation for evaluation may limit the robustness of the results. - Lack of discussion on computational efficiency and hyperparameter tuning.	sensitivity, precision, accuracy, area under ROC curve (AUC) and Specificity	-
[22]	2022	- Machine Learning (ML) classifiers: - SVM, Bagged-tree Random-	electromyography (EMG) dataset for the classification of	- LSTM achieved highest accuracy close to 99%, XGBoost	- focus on only four hand gestures, may restrict the results'	Accuracy, Recall, Precision and F1-Score.	-

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		Forest, and Extreme-Gadient-Boosting (XGBoost). - Deep Learning classifier: - Long Short Term Memory (LSTM)	hand gestures	accuracy close to 97%. - Investigates the impact of removing noisy channels. - Evaluates models on several performance measures. - Performs hyperparameter tuning	applicability to a larger range of gestures. - Lack of detailed exploration about removing noisy data channels, computing needs.		
[12]	2022	ANN: Back-Propagation Neural Network (BPNN) supported by Levenberg-Marqurdte (LM) Activation Function	cancer datasets	- BPNN + LM, showing high accuracy (97.3% matching). - ROC curves show a perfect match between true and false positive rates. - Using Different performance metrics for evaluation.	- lacks discussion on the potential limitations or challenges of using proposed method. - further validation in datasets are needed to assess performance of suggested approach of classification. - Lacks of comparison against other machine learning approaches.	MSE, ROC curves, confusion matrix	-
[18]	**2023**	Naïve-Bayes, Decision-Tree and SVM	"Lung Cancer Prediction" dataset	- Naïve-Bayes and Decision-Tree Classifiers performed comparably, showed high values in accuracy, precision, recall and F1. SVM also showed competitive performance - Include outlier analysis using Box plots.	- SVM show little bit lower performance in precision. - acknowledges limitations in dataset and models.	recall-weighted, accuracy, precision-weighted and F1-weighted	- suggesting further assessment and thorough analysis are required for more accurate and consistent lung cancer prediction.

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				- Uses different performance metrics.			
[43]	2023	deep convolutional neural networks: - AlexNet, ResNet-101, VGG-19, ResNet-50, VGG-16, InceptionV3, MobileNetv2 SqueezeNet, GoogleNet, ShuffleNet and DenseNet201	Three datasets: - (NBAIR, Xie1, Xie2) of Insect and pest identification	- Compare 11 different deep CNN. - Testing done on 3 different datasets. - Evaluation using different performance metrics. - DenseNet 201 achieved greatest test accuracy. AlexNet is well in training time, smaller architectures may benefit from ShuffleNet, MobileNet and SqueezeNet. In real-time mobile and robotics applications.	- Alex-Net, ResNet, GoogLeNet, VGG, and Inceptionv3 require large datasets, are computationally cumbersome, and not suitable for mobile applications. - lacks of discussion about parameters for each model. - Limited discussion about the datasets utilized.	accuracy, training duration, and storage requirements.	- Building Large Dataset of pests and insects. -Improve insects Segmentation from complex background. - Looking at more advanced data augmentation approaches. - Develop models that recognize insects at all life stages.
[44]	2024	remote sensing image with hardware-aware State Space Model (SSM) known Mamba (RSMamba)	three remote sensing datasets (AID, NWPU-RESISC45 and UC-Merced Land-Use)	- RSMamba is Novel, efficient architecture that outperforms modern methods based on Transformer-based and CNN models across different remote sensing datasets. - adaptations for 2D image data RSMamba has potential to serve as a backbone for future basis models.	- Inadequate theoretical analysis.	Recall, F1-score and Precision	- investigating RSMamba efficacy in other image classification tasks/domains. - Develop and test visual basis models using RSMamba as backbone.
[45]	2024	deep learning (DenseNet) + transfer learning + attention	BreakHis dataset of Breast Cancer Image	- The suggested model increase classification accuracy in comparison to	- Limited to only Binary Classification (Benign vs. malignant),	accuracy	- Optimize model architecture to decrease size

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		mechanisms (SE module)		existing methods. - Using of transfer learning improves training efficiency and minimize convergence time and handle difficulties with limited training data. - Reduce overfitting by using pre-processing and data augmentation techniques.	without taking into account cancer grades or subtypes. - The proposed model includes somewhat more parameters and that increased model size and complexity. - Limited to only one dataset. - Lacks of comparison with other state-of-art methods.		and parameter count. - ensuring accurate and interpretable models for clinical trust. - Expanding classification Capabilities to discriminating between various subtypes of breast cancer.

Performance Metrics Used for Evaluation

The common performance measures, such as Accuracy (ACC), Specificity (SP) and Sensitivity (SE). Additionally, F-measure, Kappa index (Kappa), and Area-under-curve (AUC).

Accuracy (ACC) is a statistical indicator of the percentage of correctly classified labels, ranging from 0 to 100, indicating the effectiveness of the model's classification [5] [19].

Accuracy(ACC)=(Number of correct predictions)/(Total number of predictions) …... (1)

which also can be write as:-

Accuracy(ACC)=(TP+TN)/(TP+FP+TN+FN) …………………. (2)

Where the parameters for correctness are: -

TP=True Positive (case was positive and

predicted positive)

FP=False Positive (case was negative and

predicted positive)

TN=True Negative (case was positive and

predicted negative)

FN=False Negative (case was negative and

predicted negative)

precision indicates how effectively the model can identify positives in relation to all of its positive predictions [18].

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Precision (P)=TP/(TP+FP) ……………. (3)

Recall which is additionally known as (True-Positive-Rate (TPR) / Sensitivity (SE)) measures model effectively in categorize "true positives" properly [18].

Sensitivity (SE)\TPR\Recall=TP/(TP+FN) ………… (4)

Specificity evaluates a classifier's suitability to recognize negative marks.

Specificity (SP)=TN/(TN+FP) ………..… (5) [2] [5]

area under curve (AUC) is a graph's calculated through plotting True-Positive-Rate (TPR) against False-Positive-Rate (FPR) [19].

AUC=1/2 ├ {TP/(TP+FP)+TN/(TN+FP)┤ } ………... (6) [5]

FPR=FP/((FP+TN)) …………… (7) [19]

The F-Measure/ F1 score complements the performance evaluation measure by combining recall and precision evaluations into a single metric [19].

F-Measure=(2×Precision×Recall)/(Precision+Recall) …...….. (8) [2]

Which also can be write as: -

F-Measure=(2×TP)/(2×TP+FP+FN) ……………... (9) [19]

Kappa, a statistical measure, is considered more reliable than simple accuracy due to its consideration of coincidental agreement, with a 100% probability for perfect categorization, and 0 if it is merely the result of chance [19].

Kappa=(Accuracy-Pe)/(1-Pe) …………….. (10)

Pe indicates to the theoretical probability of chance agreement given by: -

Pe=((TP+FP)×(TP+FN)+(TN+FP)×(TN+FN))/ 〖(TP+TN+FP+FN)〗 ^2 ……. (11) [19]

So, these metrics considered as the most used metrics in image classification.

Challenges and Solutions

This section discusses some common challenges that facing image classification, and proposed solutions.

Dataset Diversity

Classification can be extremely difficult due to the wide variations in images data, inability to obtain images that meet the desired criteria, also Limited data in the dataset.

Solution: - data augmentation techniques play important role for enhancing performance of model [23]. augmentation is a technique for increasing the size of a training dataset using various images "transformations". many techniques have been introduced such as using transformations like random clipping, skew, flip, translation, scaling, rotate and tilting. Another method is to create synthetic pictures using a Generative-adversarial-network (GAN) [24].

Limited Labeled Data

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The effectiveness of supervised learning models is hampered by the difficulty and expense of obtaining big, labeled datasets.

Solution: - few-shot learning and semi-supervised learning strategies showing effectiveness in overcoming the lack of labeled data [25].

Overfitting

it is a common issue in supervised machine learning, hindering model generalization. which caused by noise, limited training sets, and classifier complexity.

Solution: - Strategies likes: - early-stopping, network size reduction, data-expansion, regularization, and cross-validation, dropout. aims to prevent overfitting, exclude noises, fine-tune hyper-parameters [1].

Computational Complexit

Complex models that need a lot of processing power, such as CNNs, are harder to use.

Solution: - the use of effective model designs, which are intended to have less computational cost, such as MobileNet and EfficientNet [26].

Limited Performance

Current classification methods might not always reach the required degree of accuracy for each real word scenario.

Solution: - Continuous development led to the emergence different approaches can that greatly improve model performance such as: -

Transfer Learning

Better performance with less data may be achieved by pre-trained models (e.g., AlexNet Model) on particular tasks using large-scale datasets [1].

Hybrid / Ensemble Models

By utilizing the advantages of several techniques, combining several models into an ensemble can improve overall performance [24].

Reinforcement Learning and Semi-Supervised

Deep models are trained using a mix of un-labelled data and little labelled data. This can help with the issue of extremely unbalanced data.

Also, there are more solutions such as illustrated in [24].

Conclusion

In this study, many Image Classification Techniques have been discussed. The Most common techniques can be categories as unsupervised and supervised, conventional machine learning techniques and deep neural network. This research provides theoretical understanding of some the more popular classification techniques to choose the best possible classification strategies for your work. also also examined several challenging issues that come with image classification, such as Dataset Diversity, variability in image data,

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limited labeled data, overfitting, computational complexity, and Limited Performance. Each challenge was addressed with a corresponding solution, such as data augmentation, semi-supervised and few-shot learning, efficient model design, transfer learning, Hybrid/ Ensemble models, Reinforcement learning and Semi-supervised, etc. These solutions and continuous research and development, aim to enhance these models, hence facilitating the advancement of increasingly complex and dependable image classification techniques.

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