iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 Issue: IV Month of publication: April 2023

DOI: https://doi.org/10.22214/ijraset.2023.49851

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IV Apr 2023- Available at www.ijraset.com

A Review on Neural Approaches in Image Processing Applications

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Abstract: Image processing is the manipulation and analysis of a digitalized image; it especially improves the image quality. Also, it yields indispensable facts about the image processing techniques required for image enhancement, restoration, pre-processing, and segmentation. These methods help to provide earlier object detection and prevent further impacts due to segmentation and classification. Many reviews already exist for this problem, but those reviews have presented the analysis of a single framework. Hence, this article on Machine Learning (ML) in image processing review has revealed distinct methodologies with diverse frameworks utilized for object detection. The novelty of this review research lies in finding the best neural network model by comparing its efficiency. For that, ML approaches were compared and reported as the best model. Moreover, different kinds of datasets were used to detect the objects and unknown users or intruders. The execution of each approach is compared based on the performance metrics such as sensitivity, specificity, and accuracy using publically accessible datasets like STARE, DRIVE, ROSE, BRATS, and ImageNet. This article discloses the implementation capacity of distinct techniques implemented for each processing methods like supervised and unsupervised. Finally, the Naïve Bayes and LMS model achieved 100% accuracy as finest. Moreover, this technique has utilized public datasets to verify the efficiency. Hence, the overall review of this article has revealed a method for detecting images effectively.
Keywords: Image Processing, Machine Learning, Supervised, Image Segmentation, Image Enhancement, Unsupervised

I. INTRODUCTION

In a computer-based vision system or global analysis of the image, the low-level component part is image processing [1]. The image processing outcomes can largely affect the high-level part of the subsequent system to understand and recognize image data [2]. Machine Learning (ML) was the statistical models and scientific-based algorithms that used computer systems to perform a particular task without programming [3]. Moreover, humans used many kinds of tools to do a various tasks in image processing as simpler [4]. The human brain creativity led to different machine inventions, which made human life easy by enabling humans [5]. According to Arthur Samuel, ML is described as the study of algorithms, which is utilized to teach the machines about efficiently handling data [6]. After data viewing, the extract data's information cannot be interpreted; for that case, ML is applied [7]. With the availability of large datasets, the ML demand is high; to extract the relevant data, ML was utilized by many industries [8]. Moreover, the goal of ML is to gain knowledge from the data. To solve the data related problems, ML relies on various algorithms [9, 10]. In addition, images have played a vital role in human life because the vision is the important sense of human beings [11].

Consequently, the image processing field has various applications like military, medical, etc [12]. Nowadays, images are everywhere, and generating images in huge amounts is an easy task for everyone [13]. With such images profusion, traditional techniques for image processing have undergoes more complex issues and have to face the human vision based on their adaptability [14]. In complex vision, ML has increased as an intelligent-based computer vision program's key component when the adaptation is required [15]. With the development of benchmarks and image datasets, image processing and ML have gained much attention [16]. Moreover, innovative development of ML in image processing has a great advantage in the field that contributes a well understanding of complex images [17]. The image processing calculations with large number incorporate with some learning-based components increases the requirement of adaptation [18]. However, if the adaptation was increased then the complexity was also increased [19]. Consequently, to reduce the problems in image processing, an efficient method has to develop for controlling ML techniques [20]. Indeed, the processing of images in a huge amount means it can process the data with high dimensions and huge quantities that are problematic for ML techniques [21]. Therefore, image priors and image data interaction is required to drive the selection strategies of a model. The rest of the paper structure is described as follows: section 2 explains the different image processing techniques, section 3 describes the machine learning approaches, section 4 describes the performance and discussion of the reviewed literatures, and section 5 concludes the paper.

II. IMAGE PROCESSING TECHNIQUES

In this section, several papers are reviewed related to image processing. To improve image processing, various researchers handled different methods. Image processing techniques commonly include image preprocessing, segmentation, acquisition, restoration, data compression, object recognition, and image enhancement.

A. Image pre-processing

Image preprocessing is described as the image operations at low-level abstractions; it does not increase the information content of images but decreases it; if the entropy was an information measure [22]. The main motive of preprocessing is to improve the image data that increases the relevant features of images for other process and task analysis [63]. The different kinds of image preprocessing techniques are geometric transformations [64], brightness corrections [65], image restoration and Fourier transform [66], and image segmentation and filtering [67].

Sharma *et al*. [23] have presented an automatic detection of plant leaf disease by an artificial network. The main goal of this approach is to increase crop production in agriculture. This approach utilizes image segmentation, classification, collection, and preprocessing. Moreover, this method utilizes a Convolution-based neural network (CNN), Support Vector Machine (SVM), K-nearest neighbors (KNN), and Logistic regression. However, this model was not applicable for large datasets.

Table 1 Advantage and disadvantage of image preprocessing

Author	Year	Approach	Dataset	Advantage	Disadvantage
Sharma *et al.* [23]	2020	CNN, KNN, SVM and Logistic regression	Kaggle	The CNN has high classification and detection accuracy.	KNN and SVM do not detect accurately and the performance is poor.
Heidari *et al.* [24]	2020	VGG16-based CNN	Commonly available Medical repositories	It normalizes the noise ratio and the performance of classification is promising.	For diverse and large datasets, the design is complex.
Lu *et al.* [25]	2019	CNN-based breast cancer detection	BI-RADS	CNN accurately detects the breast cancer and preprocessing was outperformed significantly.	The CNN classifies the disease in fewer datasets and less detection accuracy.
Tang *et al.* [26]	2020	Multilayer neural-based network	MNIST	It effectively recognizes the noise, high processing speed, and high efficiency.	The need for hardware resources is high.

Heidari *et al*. [24] have developed a scheme named Computer-Aided Diagnosis (CAD) of X-ray images of chest to detect the COVID-19 infected pneumonia. The result indicated that the deep learning (DL) CAD scheme with two steps of image preprocessing and pseudo color production improves the detection accuracy. However, this approach is not promising for diverse and large image datasets. The merits and demerits of image preprocessing are represented in Table 1.

In DL, for classification, the effective technique is CNN. Lu *et al*. [25] have proposed a CNN for preprocessing breast images to detect breast cancer, which utilizes contrast limited histogram equalization, data augmentation, and median filter. The experimental results demonstrated that the presented CNN has improved image preprocessing accuracy. Moreover, the design is complex and requires more classification models.

Tang *et al*. [26] have proposed a multi-layer neural-based network by combining image pattern recognition and preprocessing. For merging, the drift memristors and integration diffusion model were developed. The result demonstrated that the model has good accuracy in noise MNIST recognition and high efficiency. However, the computational speed is high and the hardware resources requirements are high.

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B. Image Acquisition

The conversion of analog images into digital forms is known as image acquisition. In workflow sequences, image acquisition is the first step for processing [27]. Based on the work, the image acquisition process in image processing was different, and it requires long-term maintenance for hardware utilized for capturing images [68].

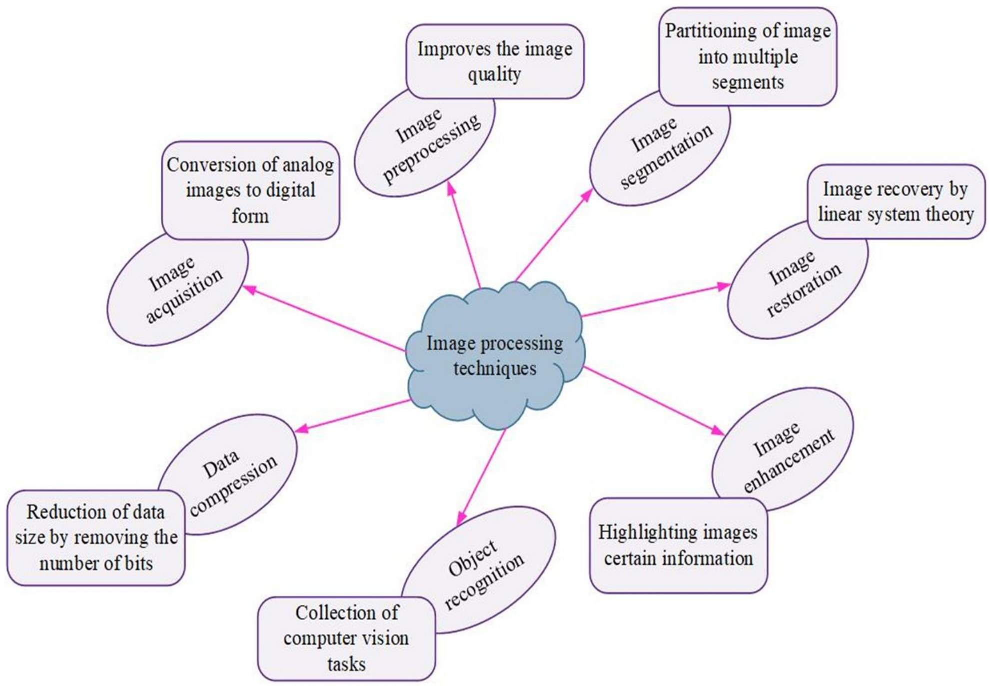

Fig. 1 Image processing techniques

Ahmad and Warren [28] have presented a Field-programmable based Gated Array's (FPGA) to implement the processing system and acquisition of deterministic latency. Moreover, the experimental outcomes showed that the overall processing time is less than other models when the input path is CPU. Furthermore, this type of simulation is not possible for different types of workloads.

Meinen and Robinson [29] have identified the unmanned aerial vehicle (UAV) image orientation effects. The presented model has increased the 3D surface model's accuracy. Moreover, for combating surface deformation, a ground-based control network was utilized. However, for landscape connectivity, erosion validation and pattern calibration were not performed well. The overall image processing techniques are shown in fig. 1.

The behavior of piglets and sows was studied by Leonard *et al*. [30] by image acquisition. Digital and depth of image system were implemented, minimal input user was developed to analyze the images, and daily and hourly postures were computed. The result demonstrated that the presented algorithm had attained higher accuracy, specificity, and sensitivity. Moreover, the processing time is high, and real-time application is not possible.

C. Image Segmentation

The process of categorization of digital images into various pixels or subgroups is known as image segmentation [69]. The image objects can reduce the image complexity, and image analysing becomes simpler. Liu *et al*. [31] have presented the Deep neural-based network (DNN); the segmentation methods of semantic images are divided into two: recent and traditional DNN method. The result indicated that the presented model has higher accuracy in segmentation. However, for dense prediction, this type of segmentation takes more time.

CNN has been commonly used to solve problems from medical fields based on image analysis and computer vision. Milletari *et al.* [32] have presented 3D CNN for image segmentation. During training, the objective function was proposed depending on the dice coefficient. The histogram matching and non-linear transformations were applied for training. Moreover, the result indicated that the presented method attained good performance, but the model is challenging and requires high-resolution images.

Zhou *et al*. [33] have presented a UNet^{++} for the segmentation of medical images. This architecture is based on a deeply-supervised encoder-decoder-based network. The decoder and encoder were connected through a nest with dense skip-pathways, which mitigates the semantic gap among sub-networks feature maps. The result indicated that UNet^{++} had attained better performance and accuracy. Moreover, using large datasets increases the running time. The performance analysis of the image processing technique is shown in Table 2.

A novel Dense-Res-Inception Net (DRINet) was presented by Chen *et al*. [34] to solve the challenging problems in CNN architecture. It contains three blocks: convolutional block, de-convolutional block and unpooling block. The multi-class segmentation i.e. CT brain images, CT abdominal images and brain tumor MR images were performed. These model improves the various and small organs segmentation and attains good results. However, this approach has some limitations, and the design is complex.

In the domain of segmentation of medical image, the effective algorithm is Genetic Algorithms (GAs) [70]. Due to artifacts and poor contrast of image, the segmentation becomes challenging [71]. Maulik *et al*. [35] have conducted a survey of GA for the segmentation of medical images. Further, the hybridization of multi-objective optimization techniques is compared with other techniques, which attains high performance. Moreover, this investigation takes more time, and the segmentation process is high.

Table 2 Performance analysis of image processing technique

Author	Approach	Dataset	Accuracy (%)
Sharma *et al*. [23]	CNN, KNN, SVM and Logistic regression	Kaggle	KNN: 54.5 CNN: 98 Logistic regression: 66.4 SVM: 53.4
Heidari *et al*. [24]	VGG16-based CNN	Commonly available Medical repositories	CNN-based CAD: 94.5
Lu *et al*. [25]	CNN-based breast cancer detection	BI-RADS	82.3
Tang *et al*. [26]	Multilayer neural-based network	MNIST	91.55
Leonard *et al*. [30]	Autonomous acquisition system	Replicated sow and piglet	97
Liu *et al*. [31]	DNN	Berkeley segmentation	85.4
Milletari *et al*. [32]	3D CNN	PROMISE 2012	-
Zhou *et al*. [33]	UNet^{++}	Lung nodule, liver, colon polyp, cell nuclei	82.9
Chen *et al*. [34]	DRINet	CT and MRI images	96.57

D. Object Recognition

Object recognition is described as computer-related vision tasks collection, which involves objects identification in digital forms [72]. Also, it is utilized for classifying or detecting objects in videos or images [73]. Chen and Kuo *et al*. [36] have presented a PixelHop: Successive-Subspace Learning (SSL) model for the recognition of object. The presented method correctly recognizes the objects for other processes. Moreover, this method is a challenging task.

The novel Elastic-Rectified-Linear-Unit (EReLU) was proposed by Jiang *et al*. [37] for processing the positive input part. EReLU is categorized by each value scales as positive during the training stage. Moreover, they also presented an Elastic Parametric ReLU (EPReLU) for improve the network's performance. The experimental results demonstrated that the presented method had attained higher performance. Moreover, it is valid for the training of images.

Table 3 Performance of object recognition method

Sl.no	Author	Approach	Dataset	Accuracy (%)
1	Chen and Kuo *et al.* [36]	PixelHop: SSL model	MINST	99.09
			Fashion MINST	91.68
			CIFAR-10	72.66
2	Li *et al.* [39]	graph-based saliency method and grabCut-based optimization framework	MSRA	91.67
3	Sudharshan and Raj [40]	CNN on Keras	CIFAR 10	96
4	Surantha and Wicaksono [41]	SVM and Histogram-of-Gradient (HoG)	Common available images	89
5	Prystavka *et al.* [42]	ANN, classifying perceptrons and convolutional autoencoders	Image collection	97.5

Bapu *et al.* [38] have proposed an adaptive CNN model by N-gram for satellite images spatial recognition of the object. N-gram utilizes the learning models functionalities that image in structure gathers the data by prior knowledge. The result demonstrated that the presented method detects object and satellite images with dissimilar level recognition. However, the running time and design complexity are high for larger datasets.

Li *et al.* [39] have presented a graph-based saliency method and grabCut-based optimization framework for object recognition. It automatically extracts the foreground objects. The pixel shrink and separate pixelization are utilized to increase the foreground objects. The result demonstrated that it automatically extracts and the object recognition performance was significantly improved. Moreover, the extraction takes more time and requires a high-density. The performance of object recognition is illustrated in the Table 3. Detection of objects from the image repository is a difficult task in the computer vision area [74]. Sudharshan and Raj [40] have presented a CNN on Keras for detection and classification of the object. The CIFAR 10 dataset with 60,000 images is trained to the system for detection. The presented model showed that CNN had earned 96% accuracy for recognition. Moreover, the classification takes more time and the design is complex.

Surantha and Wicaksono [41] have implemented and designed a home-based security system. It was implemented by Arduino and Raspberry Pi 3 that are connected using the USB cable. The object recognition is done by SVM and Histogram-of-Gradient (HoG). Moreover, the presented model easily detects suspicious objects with precise accuracy. However, the detection of the intruder has lesser detection than object detection.

Prystavka *et al.* [42] have presented aerial image recognition and processing method depending on the artificial-based neural network (ANN), specifically, classifying perceptrons and convolutional autoencoders. The presented model has higher classification efficiency, and it automatically generates image recognition. Moreover, a large number of implementations are required for this process.

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E. Image Restoration

Image restoration is described as the task of image recovery from the degraded version by assuming some degradation phenomenon knowledge [75]. It models the process of degradation and inverts it to attain the original form from the degraded image [76]. Moreover, it does not fully depend on the degradation nature [77]. With the advancement of information-based computer technology and information technology, the acquisition mode of information is mostly converted from the character to certain image nowadays [78].

Moreover, in the transmitting acquiring image process, image quality were decreased and damaged because of various factors [79]. To end this, Xue and Cui [43] have presented an image restoration method depending on the BP-neural network. Further, the result of this method indicated that it has greatly improved than the traditional-based image restoration model. However, the design is complex, and computation time is more.

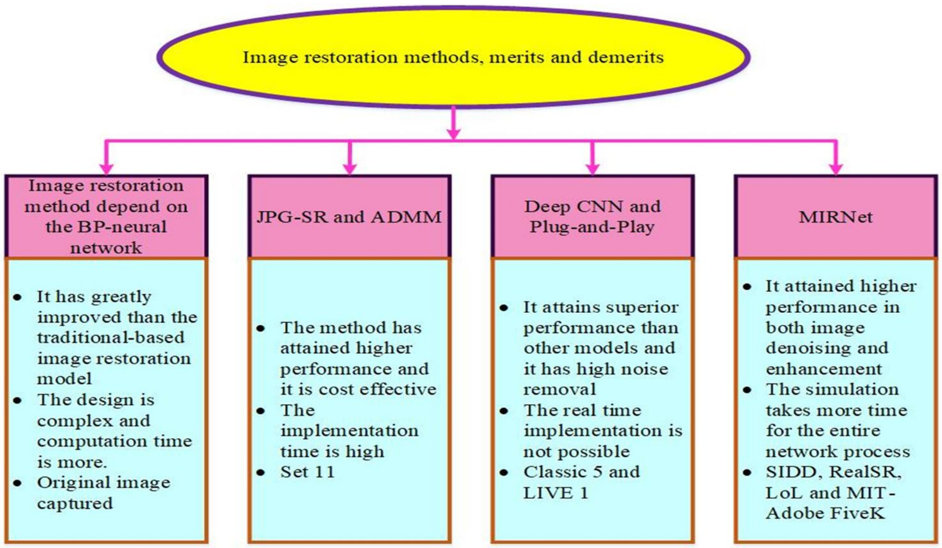

Fig. 2 Image restoration method performance

In various computer vision-based tasks and image processing, the Sparse Representation (SR) had attained great success [80]. In image processing, Patch-based SR (PSR) methods usually generate undesirable artifacts in visual [81]. Further, the group-based SR (GSR) generates over-smooth effects [82]. Zha *et al.* [44] have proposed a new SR model i.e. Joint Patch-group SR (JPG-SR). It includes image deblocking and inpainting in the tasks of image restoration. Moreover, the Alternating Direction Methods for Multipliers (ADMM) model was developed. The result of the method has attained higher performance and is cost-effective. However, the implementation time is high. The overall image restoration method's merits and demerits are shown in fig. 2.

Zhang *et al*. [45] have proposed a deep CNN with a larger capacity to model Plug-and-Play-based image restoration. The deep-denoiser prior were removes the noises in the images for better restoration of images. The task includes super-resolution, demosaicing, and deblurring. Moreover, the presented method attains superior performance than other models, and it has high noise removal. However, real time implementation is not possible.

Zamir *et al*. [46] have presented the novel CNN with spatially-precise high-resolution images for the entire network i.e. MIRNet. The approach has various key elements: exchange of information through multi-resolution streams, parallel convolution streams, multi-scale aggregation feature attention and capturing contextual information by channel and spatial attention. The result has attained higher performance in both image denoising and enhancement. However, the simulation takes more time for the entire network process.

F. Image Enhancement

Image enhancement is described as the process of quality improvement and original data information content before processing [83]. Moreover, it highlights the image's certain informations and remove the unnecessary information as per particular needs [84]. Islam *et al*. [47] have presented an adversarial network model based on conditional generative (GAN) for image enhancement of real-time underwater-based images.

Moreover, the EUVP dataset was used for unpaired and paired underwater image collection. The real-time result has attained higher performance, and it has been able to perform the validation as quantitative and qualitative. However, the color stability and consistency were not trained well for unpaired collections.

Oktay *et al.* [48] have presented the automatically-constrained-neural-based networks (ACNNs) for cardiac image segmentation and enhancement. The new presented framework encourages the methods to follow the underlying anatomy's anatomical properties.

The result has indicated that the ACNNs improved the prediction accuracy and demonstrated the 3D-shapes deep models for classification. However, the real-time implementation is not done, and minute errors affect the accuracy.

Qiu *et al.* [49] have proposed a Frequency-band-broadening (FBB) and CNN for image enhancement. The medical image edges are wiped off by the cycle spinning scheme. In addition, pixel-level-based fusion is done among two enhanced images from FBB and CNN. The result of the presented method has significantly enhanced and provides more accurate and effective results for disease diagnosis. However, the variation in images affects the prediction accuracy.

Salem *et al*. [50] have presented histogram algorithms for image enhancement in medical images. The power MATLAB is utilized to analyze the image enhancement performance of the presented study. Furthermore, it compares the results with other performance based on three metrics i.e., standard deviation, the ratio of peak signal and noise, and error rate.

G. Convolutional Neural-based Network (CNN) and Fuzzy-based image classification

Several papers are reviewed in this section related to image processing methods. Diverse researchers handled different methods to improve the methods of image processing for better precise results. The most utilized technique by the researchers is the Convolution Neural Network (CNN); also, this CNN has earned better results with the presence of a Support Vector Machine (SVM).

To extract and classify the abnormal cells of the brain, Krishnakumar and Manivannan [51] have developed a Gabor wavelet model with different features. The key reason for this proposed model is to extract the abnormal cell features with a high exactness rate. Hereafter, the kernel-based support vector model is employed to specify the tumor types. In addition, the fitness of fruit fly was used with the Gabor wavelet model to gain a good outcome. Finally, it has earned the finest outcome; however, it is hard to design for brain structures.

Sasank and Venkateswarlu [52] have designed a contrast histogram-based Laplacian of Gaussian model for the abnormal cell features extraction from the trained MRI brain images. In addition, the Soft plus extreme learning with the use of kernel features was used to specify the tumor types. Here, the segmentation process has yielded a very good outcome. But it has gained fewer prediction measures for tumor type specification.

In the ML field, the Fuzzy models have played an important role in decision making or the prediction mechanism. So, Kumar *et al*. [53] have introduced the Fuzzy c-means algorithm in the medical imaging system. Here, the brain MRI images are taken from the BRATS MICCAI database and imported into the system. Then the fuzzy model was developed to classify whether the brain images were normal or contained any tumors. It has attained the finest prediction accuracy. But segmentation of brain tumors is not done.

To identify the tumor severity level in the brain, differentiating the non-tumor and tumor cells is the most crucial task in medical imaging. So, Kumar *et al.* [54] have designed a convolution neural model with an optimization strategy to classify the abnormal tumors. Finally, it has reported 96% of classification accuracy. However, it can't predict the exact tumor cell presented region in the brain image. The review of literature performance is shown in fig. 3.

Raja [55] has structured Bayesian fuzzy procedures in a deep autoencoder model to segment the tumor cell from the MRI brain. In addition, the optimization called java is used to specify the tumor types. Finally, the designed paradigm has earned a 98.5% exactness rate for tumor classification. However, the designing process has required more time to execute.

On the other hand, the imaging technique called Optical Coherence Tomography (OCT) was used by Ma *et al.* [56]. It is one of the invasive imaging techniques, and utilized the ROSE dataset to check the proficient score of the OCT for the retinal image segmentation process.

Here, for better visualization of the affected part, a map was drawn for target and source images. Consequently, it has earned 96% accuracy and 90% sensitivity, but it has consumed more power.

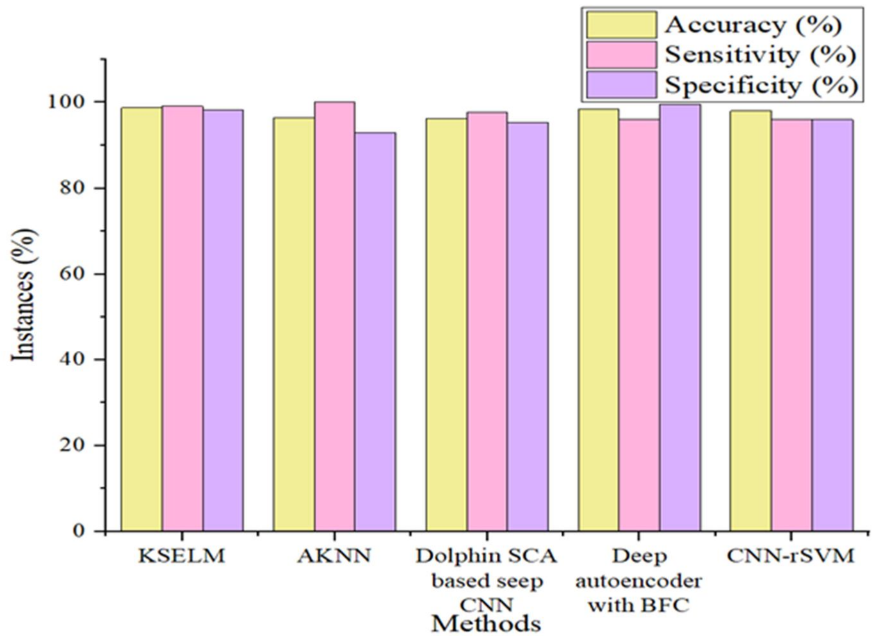

Fig. 3 Review of literature performance

Ghosh and Ghosh [57] have presented CNN with a ranking SVM (CNN-rSVM) model to segment the blood vessels in the retina images. Hence the combination of deep neural convolution model with support vector classification has afforded the best result by gaining 98% accuracy and 96% sensitivity rate. However, it has taken more time to execute while compared to normal CNN.

III. MACHINE LEARNING APPROACHES

ML approaches are selected based on the problems, and broadly classified into eight categories [85]. Moreover, many programmers and mathematicians apply various approaches to identify the solution for ML-based problems with huge datasets. In addition, the different ML algorithms are shown in fig. 4.

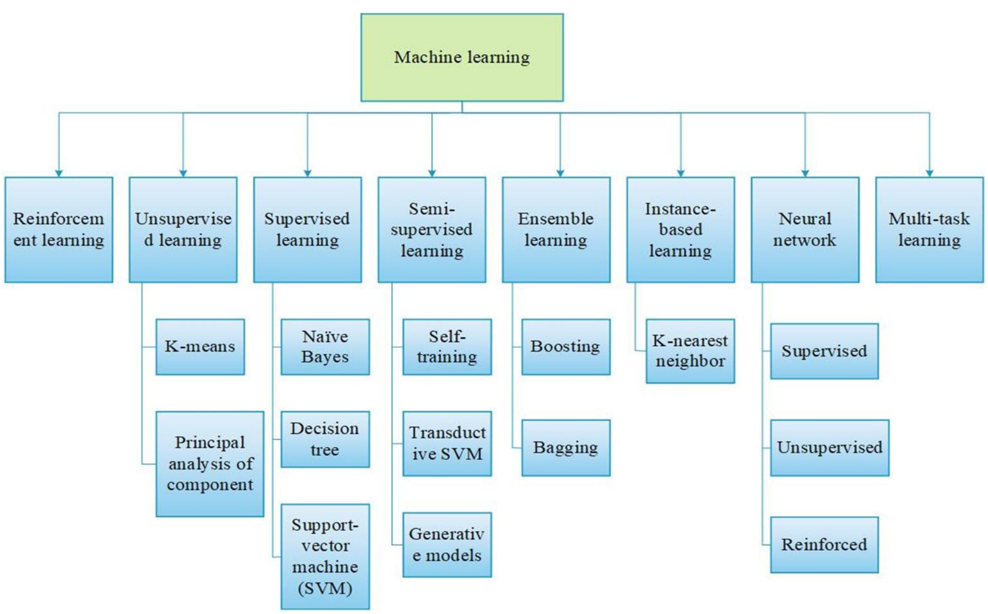

Fig. 4 ML approaches

The ML approaches involve neural-network-based approaches [86], mathematical modeling methods [87], KNN [88], etc. were discussed below. Normally, the supervised approaches in the segmentation process are identified to be more effective than the unsupervised approaches in terms of their performance, including high expenses and time-consuming purposes [89].

A. Supervised Model

Supervised methods in image processing classify the images based on the pixels of images [90]. The main motive of this method is to attain the optimal image with quality [91]. The halftone image classification is largely demanded to attain high-quality images for halftoning method [92]. Liu *et al*. [58] have proposed a Naïve Bayes and Least-mean square (LMS) algorithm for image classification. The presented method has earned 100% accuracy, and the performance is effective. Moreover, the execution time is high for both algorithms, and the design is complex.

Prinyakupt and Pluempitiwiriyawej [59] have presented linear and naïve Bayes classifiers for white blood cells (WBC) segmentation by digital image processing. The process of segmentation combined morphological operation, ellipse-curve fitting, and thresholding. The result of the presented method has attained higher performance in both segmentation and classification and offers better results. Moreover, the linear classifier takes more time for execution.

The internet has changed the way of communication that has become more concentrated on images and emails. Harisinghaney *et al*. [60] have implemented three algorithms: Naïve Bayes, reverse DBSCAN, and KNN algorithm. It utilizes a spam datasets named Enron corpus's and ham emails. Moreover, the presented method has attained higher accuracy, specificity, and sensitivity. However, the presented model does not identify threats and viruses found in an email.

In the Indonesian development of the economy like export industries, micro industries, and domestic industries, the fisheries have contributed more in which the main fishery product is Tuna [93]. To generate the tuna-fish product, the industries were separate the tuna according to their type [94]. Khotimah *et al*. [61] have presented an automatic classification of tuna fish by image processing and decision tree method. The features of the fish are validated for better classification. Moreover, the presented model has earned 88% accuracy, and it has better classification results. However, the presented method has lesser accuracy than other methods. Modern detection of plant disease and phenotyping provides promising steps towards sustainable agriculture and food security [95]. In particular, computer vision and image-based phenotyping provide the capability to study the physiology of quantitative plant [96]. However, the amount of work is highly tremendous for manual interpretation [97]. Islam *et al.* [62] have presented an SVM and image processing to classify the disease. The segmentation results indicated that the SVM has higher accuracy in disease diagnosis. Moreover, the disease diagnosis takes more time. Normally, vessel segmentation using retinal images is difficult because of the presence of pathologies, intricate vessel topology, and lower contrast of blood vessels. To reduce these issues, Mo *et al.* [98] introduced the neural network-based model for performing the process of vessel segmentation. Also, Fraz *et al.* [99] introduced a new approach by combining the image extracting techniques to transform morphology, measure line strength, etc. A 17-D feature vector was used in this method and was computed for different configurations to monitor their responses. The accuracy of this method was evaluated with DRIVE and STARE datasets. The accuracy of supervised models is shown in fig. 5.

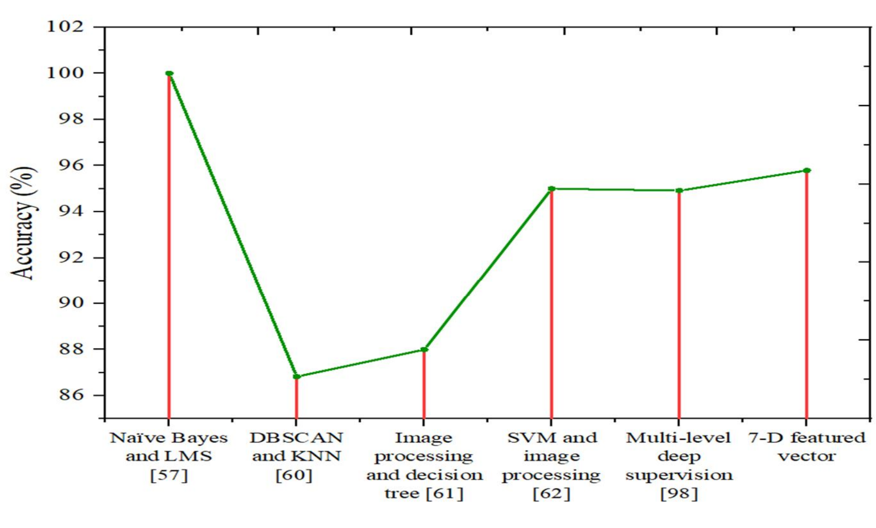

Fig. 5 Accuracy of supervised models

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IV Apr 2023- Available at www.ijraset.com

B. *Unsupervised Model*

Segmentation of image is described as the image classification into various groups [103]. The popular method for segmentation is the K-means clustering algorithm, which was an unsupervised algorithm [104]. Dhanachandra *et al*. [100] have presented K-means and Subtractive clustering algorithms to improve the image quality for segmentation. The median filter is implemented to the segmented image to eliminate the unwanted area from the images. Moreover, the presented method has achieved better outcomes. Moreover, the analysis is difficult for image segmentation.

Alhussein *et al.* [101] have designed a retina segmentation model for classifying glaucoma and diabetic range of the patients. The purpose of this presented model is to identify and prevent diseases in earlier; to execute the process; an unsupervised model (UM) was designed. Therefore, the gained accuracy was 95%, and sensitivity was 87% for the dataset Drive and CHASE. However, based on the dataset, the designing process has taken more duration.

In various applications and fields, clustering algorithms have been successfully implemented as image segmentation [105]. Moreover, those algorithms are only suitable for particular images such as microscopic images, medical images etc. [106]. Sulaiman and Isa [102] have presented an adaptive Fuzzy-K-means (AFKM) algorithm for the segmentation of images. The results indicated that the presented model has the better visual quality and higher segmentation. Moreover, the design process takes more time.

IV. PERFORMANCE EVALUATION

The performance of image processing methods is measured regarding image pixels [107]. So image pixels are differentiated for normal and digital images or backgrounds [108]. Four classifications are available for analysis. The result analysis of segmentation methodologies is observed regarding their parameters like sensitivity [109], specificity [110], and accuracy [111]. Here, sensitivity is the measurement of true positive values identified accurately, which denotes the ratio of true positive value of identified images to the sum of true positive and false negative values. Sensitivity (S) is measured using Eqn. (1).

$$S = {\tilde{T}_p} \Big/ {\tilde{T}_p + \tilde{F}_n} \tag{1}$$

Moreover, the calculation of specificity is the measure of the true negative rate that represents the proportion of wrongly classified image pixels to the summation of true negative and false positive values. Specificity measure is calculated using Eqn. (2).

$$Specificity = \frac{\tilde{T}_n}{\tilde{F}_p + \tilde{T}_n} \tag{2}$$

Subsequently, accuracy (A) is the proportion of the total quantity of properly identified pixels while processing the entire pixels obtained and is calculated using Eqn. (3).

$$Accuracy = \frac{\tilde{T}_p + \tilde{T}_n}{\tilde{T}_n + \tilde{T}_p + \tilde{F}_p + \tilde{F}_n} \tag{3}$$

These analyses are made based on $\tilde{T}_p$ and $\tilde{T}_n$ represents the true positive and true negative rate and $\tilde{F}_p$ and $\tilde{F}_n$ represents the false positive and false negative rate. Here, $\tilde{T}_p$ is the measure of pixels rightly, $\tilde{F}_n$ denotes the sum of pixels wrongly differentiated as background, $\tilde{T}_n$ is the measure of rightly identified pixels as background, and $\tilde{F}_p$ represents the wrongly identified images. Moreover, the overall performance of the machine learning models is shown in Table 4.

In addition, the accuracy of the overall methods are compared with other methods such as unsupervised model [101], Naïve Bayes and LMS [58], ACNNs [48], MIRNet [46], JPG-SR and ADMM [44], B-P Neural network (B-PNN) [43], ANN [42], SVM and HoG [41], CNN on keras [40], GrabCut Optimization (GCO) [39], SSL [36], DRINet [34], UNet^{++} [33], DNN [31], autonomous acquisition system (AAS) [30], Multilayer neural network (MNN) [26], CNN [25], VGG16-CNN [24].

The overall comparison of accuracy, sensitivity, and specificity is shown in fig. 6 and 7, respectively. In addition, the performance of the sensitivity and specificity of unsupervised model [101], autonomous acquisition system (AAS) [30], CNN [25], and VGG16-CNN [24] are compared with each other.

Table 4 Overall performance analysis

Author	Year	Approach	Dataset	Advantage	Disadvantage
Leonard *et al.* [30]	2019	Autonomous acquisition system	Replicated sow and piglet	High accuracy in autonomous system acquisition	Computational time is high
Liu *et al.* [31]	2019	DNN	Berkeley segmentation	Segmentation is more accurate and higher speed	Computational time or running time is high
Milletari *et al.* [32]	2016	3D CNN	PROMISE 2012	It improved the convergence time and results	It requires high resolution images for process
Zhou *et al.* [33]	2018	UNet^{++}	Lung nodule, liver, colon polyp, cell nuclei	More accurate results in segmentation of the medical image	The segmentation process takes more time for large datasets
Chen *et al.* [34]	2018	DRINet	CT and MRI images	The segmentation accuracy is high, and it is applicable for both small and large datasets	Complexity is high in design and limitations for some parameters
Maulik *et al.* [35]	2009	GA	-	Attains high performance and segmentation	Investigation takes more time and segmentation process is high
Chen and Kuo *et al.* [36]	2020	PixelHop: SSL model	MINST, Fashion MINST, and CIFAR-10	It correctly recognizes the objects and it has high accuracy	The running time is high and design is challenging
Jiang *et al.* [37]	2020	EReLU and EPReLU	CIFAR10, Image Net and SVHN	Attained higher performance	Valid for training of images
Bapu *et al.* [38]	2019	CNN model by N-gram	-	Precise detection of object and satellite images dissimilar level recognition	The running time and design complexity is high for large datasets
Li *et al.* [39]	2018	graph-based saliency method and grabCut-based optimization framework	MSRA	It automatically extracts and the object recognition performance was significantly improved.	The extraction takes more time and requires high-density
Sudharshan and Raj [40]	2018	CNN on Keras	CIFAR 10	CNN has earned higher accuracy for recognition	The classification takes more time and the design is complex
Surantha and Wicaksono [41]	2018	SVM and Histogram-of-Gradient (HoG)	-	The presented model easily detects the suspicious objects with precise accuracy	The detection of intruder has lesser detection than object detection
Prystavka *et al.* [42]	2020	ANN, classifying perceptrons and convolutional autoencoders	Image collection	Higher classification efficiency and it automatically generates the image recognition	Large number of implementations is required for this process
Xue and Cui [43]	2019	Image restoration method depend on the BP-neural network	Original image captured	It has greatly improved than the traditional-based image restoration model	The design is complex and computation time is more
Zha *et al.* [44]	2020	JPG-SR and ADMM	Set 11	The method has attained higher performance and it is cost effective	The implementation time is high
Zhang *et al.* [45]	2021	Deep CNN and Plug-and-Play	Classic 5 and LIVE 1	It attains superior performance than other models and it has high noise removal	The real time implementation is not possible
Zamir *et al.* [46]	2020	MIRNet	SIDD, RealSR, LoL and MIT-Adobe FiveK	It attained higher performance in both image denoising and enhancement	The simulation takes more time for the entire network process
Islam *et al.* [47]	2020	GAN,	EUVP	It has attained higher performance and it has able to perform the validation as	The color stability and consistency was not trained well for unpaired

				quantitative and qualitative	collections
Oktay *et al*. [48]	2017	ACNNs	ImageNet	ACNNs improved the accuracy of prediction and demonstrated the 3D-shapes deep models for classification	The real-time implementation is not done and minute errors affect the accuracy
Qiu *et al*. [49]	2019	FBB and CNN	Medical-image	It significantly enhanced and provides more accurate and effective results for disease diagnosis	The variation in images affects the prediction accuracy
Sasank and Venkateswarlu [52]	2021	KSELM	BRATS	Very good outcome in segmentation	Fewer prediction measures for tumor type classification
Kumar *et al*. [53]	2021	AKNN	BRATS MICCAI	Finest prediction accuracy	Brain tumor segmentation is not done
Kumar *et al*. [54]	2020	Dolphin SCA based seep CNN	BRATS	Classification accuracy is high	It doesn't predict the exact tumor cell presented region in MRI
Raja [55]	2020	Deep autoencoder with BFC	BRATS 2015	Exactness rate for classification of tumor	Computational time is high
Ma *et al*. [56]	2020	OCT	ROSE	It has attained better performance and provides precise outcomes	It has consumed more power
Ghosh and Ghosh [57]	2021	CNN-rSVM	Public dataset	Support vector classification has afforded the best result by gaining 98% accuracy and 96% sensitivity rate	It has taken more time to execute while compared normal CNN
Liu *et al*. [58]	2011	Naïve Bayes and LMS	-	It has attained higher accuracy and the performance is effective	The execution time is high for both algorithms and the design is complex
Prinyakupt and Pluempitiwiriyawej [59]	2015	Linear and naïve Bayes classifier	CellaVision.com	It has attained higher performance in both segmentation and classification and offers better results	The linear classifier takes more time for execution
Harisinghaney *et al*. [60]	2014	Naïve Bayes, reverse DBSCAN and KNN algorithm	Enron corpus's and ham emails	The presented method has attained higher accuracy, specificity and sensitivity	The presented model has does not identifies threats and viruses found in email
Khotimah *et al.* [61]	2014	Image processing and decision tree	Fish dataset	The presented model has earned 88% accuracy and it has better classification results	It has lesser accuracy than other methods
Islam *et al.* [62]	2017	SVM and image processing	Publicly available images	SVM has higher accuracy in disease diagnosis	The disease diagnosis takes more time
Mo *et al.* [98]	2017	Multi-level deep supervision	DRIVE	This approach reduced the effects of subjective factors	This model increased the complexity for performing segmentation
Fraz *et al.* [99]	2011	7-D featured vector	STARE	It effectively classified retinal images into two categories of pixels that are non-vessel and vessel.	The classifier needs more time to differentiate the segmented images as vessel or non-vessel.
Alhussein *et al.* [101]	2020	Unsupervised model	DRIVE and CHASE	The presented model has higher performance and effective outcomes	The designing process has taken more duration

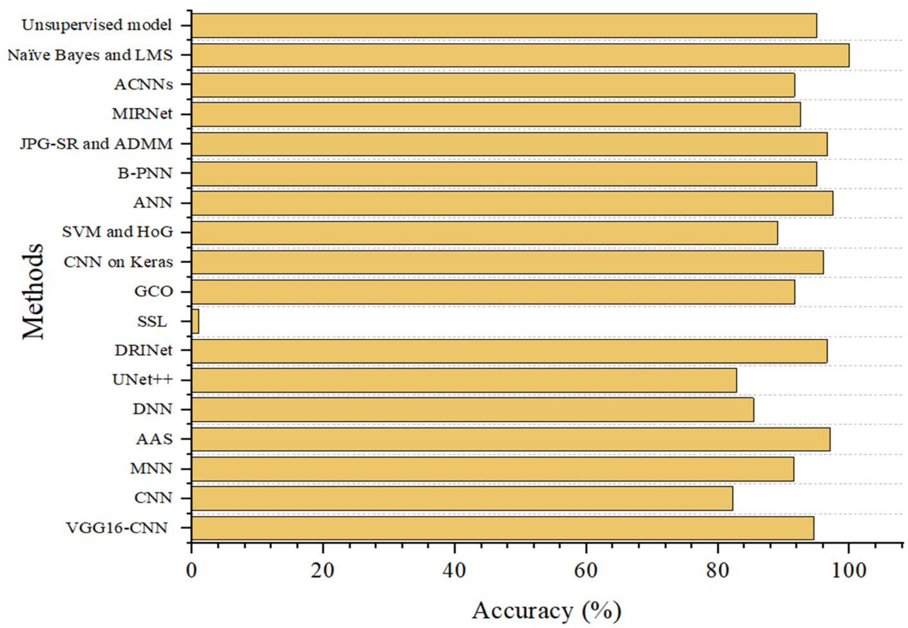

Fig. 6 Overall comparison of accuracy

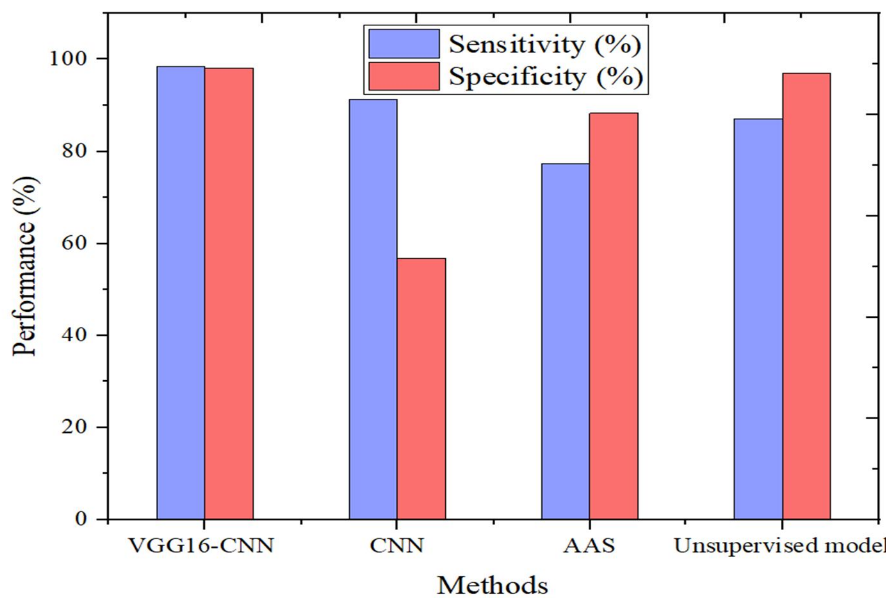

Fig. 7 Overall comparison of sensitivity and specificity

A. Discussion

The machine learning approaches in the image processing methods were investigated and analyzed to identify the efficiency of the developed approaches. This work has detailed a review of the recent image processing techniques involving supervised and unsupervised ML methods. These methods have utilized several datasets like DRIVE, STARE, BRATS, ImageNet, etc. In addition, the Naïve Bayes and LMS model [58] has earned 100% accuracy for image segmentation. Also, the accuracy of the approach following CNN-based methods [24], AAS [30], DRINet [34], SSL [36], ACNNs [48], and unsupervised model has attained above 94% accuracy and performs better results than other models. Generally, the supervised ML methods are found to be more efficient for performing image processing than unsupervised methods because of their high expense and time consumption.

Also, in some cases, the insufficiency data might cause overfitting issues. Hence if the overfitting issues are raised, then that issues

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IV Apr 2023- Available at www.ijraset.com

were solved using the regulation techniques. In other words, if the datasets have fewer images, then the algorithm needs to be designed with a regulation approach, which is known as data augmentation. Moreover, the attained accuracy by various methods is shown in Table 5.

Table 5 Accuracy of overall reviewed literatures

Author	Approach	Accuracy (%)
Sharma *et al.* [23]	CNN, KNN, SVM and Logistic regression	CNN: 98
Heidari *et al.* [24]	VGG16-based CNN	94.5
Lu *et al.* [25]	CNN-based breast cancer detection	82.3
Tang *et al.* [26]	Multilayer neural-based network	91.55
Leonard *et al.* [30]	Autonomous acquisition system	97
Liu *et al.* [31]	DNN	85.4
Zhou *et al.* [33]	UNet^{++}	82.9
Chen *et al.* [34]	DRINet	96.57
Chen and Kuo *et al.* [36]	PixelHop: SSL model	99.09
Li *et al.* [39]	graph-based saliency method and grabCut-based optimization framework	91.67
Sudharshan and Raj [40]	CNN on Keras	96
Surantha and Wicaksono [41]	SVM and Histogram-of-Gradient (HoG)	89
Prystavka *et al.* [42]	ANN, classifying perceptrons and convolutional autoencoders	97.5
Xue and Cui [43]	Image restoration method depend on the BP-neural network	95
Zha *et al.* [44]	JPG-SR and ADMM	96.56
Zamir *et al.* [46]	MIRNet	92.56
Islam *et al.* [47]	GAN,	
Oktay *et al.* [48]	ACNNs	91.6
Sasank and Venkateswarlu [52]	KSELM	98.75
Kumar *et al.* [53]	AKNN	96.5
Kumar *et al.* [54]	Dolphin SCA based seep CNN	96.3
Raja [55]	Deep autoencoder with BFC	98.5
Ma *et al.* [56]	OCT	96
Ghosh and Ghosh [57]	CNN-rSVM	98
Liu *et al.* [58]	Naïve Bayes and LMS	100
Harisinghaney *et al.* [60]	Naïve Bayes, reverse DBSCAN and KNN algorithm	86.83
Khotimah *et al.* [61]	Image processing and decision tree	88
Islam *et al.* [62]	SVM and image processing	95
Mo *et al.* [98]	Multi-level deep supervision	94.92
Fraz *et al.* [99]	7-D featured vector	95.79
Alhussein *et al.* [101]	Unsupervised model	95

However, the investigated approaches have many limitations like less accuracy, high false detection rate, high time utilization, and less performance [112, 113, 114]. Therefore, these limitations should be minimized to attain better output with high performance. In the future, DL with hybrid optimization methods can help to improve the image processing process and to enhance efficiency while reducing the fault detection rate.

Already many approaches are available with the combination of DL and ML optimization, but still, it has recorded poor performance in some cases because of algorithm weakness. Hence, the hybridization of the algorithm can compensate the one weakness parameter with another optimization algorithm. Hereafter, it has applied a DL dense layer that will yield the finest performance compared to other models.

V. CONCLUSION

Image processing by ML has a major contribution for image segmentation, pre-processing, enhancement, restoration etc. Here, STARE, DRIVE, ROSE, BRATS, and ImageNet datasets were used to pattern images. Moreover, the importance of image processing by ML approaches is discussed. Various methods available for image processing and the techniques applied to each method were also analyzed. The execution rate of these approaches is analyzed regarding sensitivity, specificity, and accuracy. The study carried out the image processing and ML techniques following supervised and unsupervised methods proved to have a good performance. Also, the public dataset has provided a good comparison for the fundus images, as it contains more images. So, in the future, a hybrid optimized DL method incorporated with the Public dataset is better for standard research; it will provide better image processing, segmentation, pre-processing, and enhancement. Moreover, the use of a public dataset helps to improve the image processing methods and reduces the image complexities.

A. Acknowledgement

None

B. Compliance with Ethical Standards

1) Disclosure of Potential Conflict of Interest:

The authors declare that they have no potential conflict of interest.

2) Statement of Animal and Human Rights

3) Ethical Approval

All applicable institutional and/or national guidelines for the care and use of animals were followed.

4) Informed Consent

For this type of analysis formal consent is not needed.

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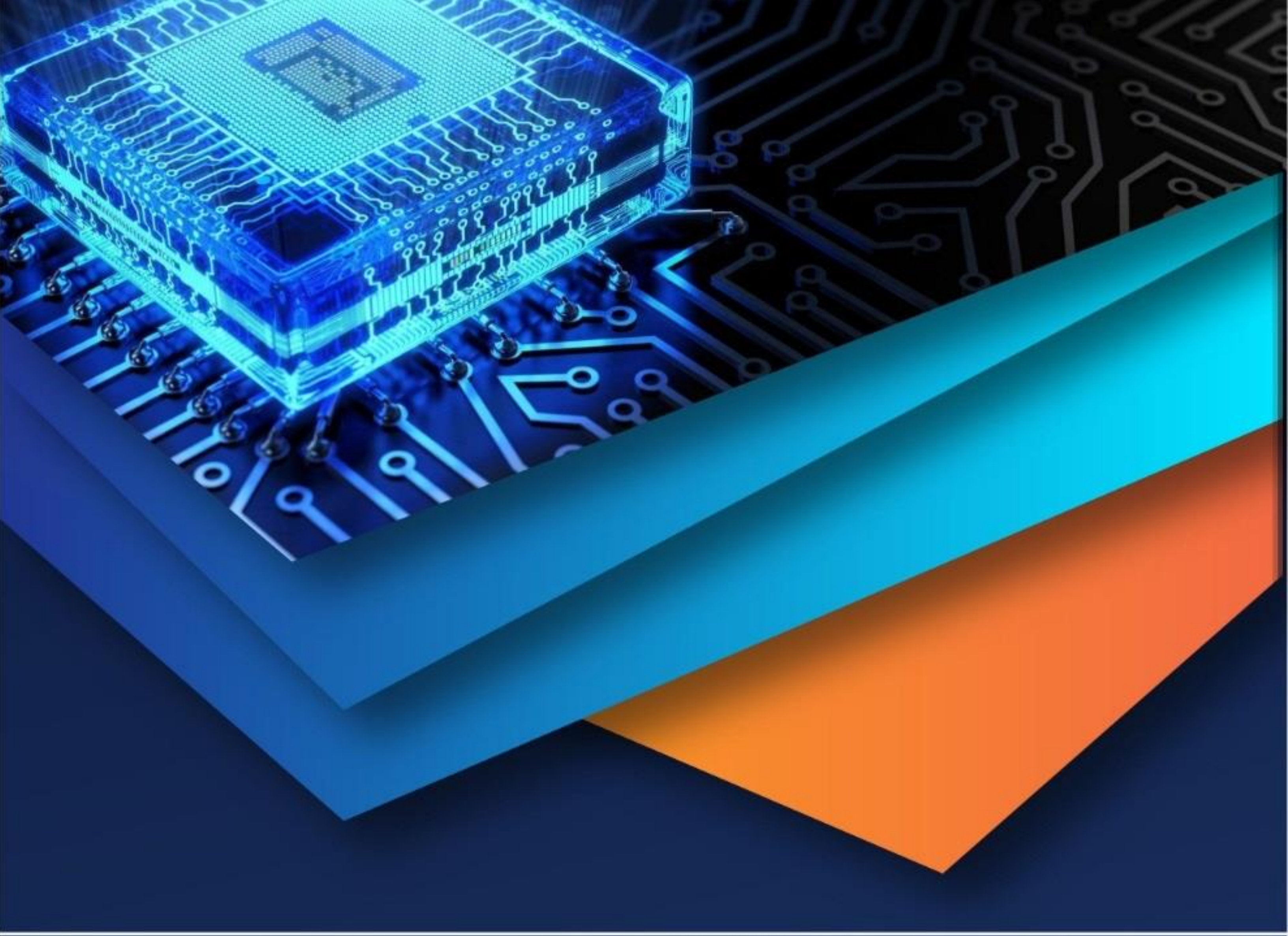

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