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HD-CNN: Early-stage Alzheimer Detection system using Hybrid Deep Convolutional Neural Network

Dr. Sunil S. Khatal *, [2] Dr. Krishna Prasad K

[1] Research Scholar, Department of cyber security and cyber forensics, Institute of Engineering and Technology Srinivas University
[2] Guide, Professor and Head, Department of cyber security and cyber forensics, Institute of Engineering and Technology Srinivas University

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ABSTRACT
According to recent predictions, Alzheimer disease (AD), which is presently the sixth greatest cause of impermanence in the USA, may come in third place among all causes of death for seniors, just after cancer and heart disease. It is obvious that it is crucial to identify this illness early and stop it from spreading. Numerous medical tests are necessary for the diagnosis of Alzheimer disease (AD), which generates enormous amounts of multivariate heterogeneous data. The varied nature of medical testing makes it difficult and taxing to manually compare, evaluate, and analyze this data. In this research we proposed an early-stage detection AD using hybrid deep learning algorithms. The various feature extraction and selection methods are used for extraction of potential features. The RESNET-101 and VGGNET are the deep learning frameworks that we use for classification. The YOLOv8 is used for data preprocessing as well as object detection. The RESNET-101 obtains higher 99.35% accuracy with 100 epoch size and 15 hidden layers which is higher than all experiments. In comparative analysis our model evaluation has done with VGGNET and ShallowNet, As a result our system outperforms higher result than both.

KEYWORDS
Alzheimer's disease, deep learning, biomarkers, positron emission tomography, Magnetic Resonance Imaging, mild cognitive impairment

1. Introduction

The word "dementia" refers to a range of diseases that may damage brain cells and cause gradual, permanent memory loss in humans. Alzheimer's disease, the most common form of dementia, is classified into these three levels based on its severity: mild, moderate, and severe [1]. Patients with Alzheimer's disease are reported to undergo a gradual loss of cognitive function throughout the course of the illness, culminating in a complete loss of memory and an inability to do even the most basic of tasks [13, 14, 16, 17, 25, 26]. The most common type of dementia, Alzheimer's disease is the sixth leading cause of mortality worldwide. As much as 80% of dementia cases may be attributed to it. The number of people living with Alzheimer's disease is expected to almost triple, from 5 million in 2014 to 14 million in 2060, as predicted by the Centers for Disease Control and Prevention (CDC). Despite its prevalence, this degenerative illness is still untreatable [18, 19, 20].

Magnetic resonance imaging (MRI) techniques like diffusion tensor imaging [18] have been shown to be beneficial for studying the brain's white matter structure. DTI is one of many imaging approaches that have been used to identify and study Alzheimer's disease [21, 22]. DTI is a noninvasive imaging technique that uses the Brownian motion of water molecules as its foundation. It may be used to learn more about the distribution of water molecules in tissues, including their size, anisotropy, and spatial orientation.

MRI scans of the brain are used to diagnose Alzheimer's disease based mostly on the presence of cerebral atrophy, the shrinking of brain tissue caused by the loss of gray and white matter in the proximal temporal and temporoparietal cortical lobes. In addition, Alzheimer's disease brain structural abnormalities may be quantified using the classification of brain MRIs obtained at different stages. However, clinicians may struggle with manual data collection and processing from large, complex DTI datasets. Furthermore, inter- or intra-operator variation concerns might make mechanical examination of brain DTIs extremely time-consuming and inaccurate. One approach to completely automating the DTI assessment process isto use existing automated techniques for MRI classification, representation, and registration. Because of this, accurate data may be generated with more assurance [13].

Brain MRI segmentation is considered crucial in a wide range of medical applications because of the effect it has on the entire investigation's findings. Measurement and visualization of brain structures, lesion identification, and image-guided therapies and surgeries are some of the most common uses of MRI segmentation. The fundamental purpose of brain MRI delineation is to divide an image into distinct regions, each of which is made up of pixels with the same tonal range and texture as the rest of the image.

There have been many presentations of deep learning techniques to aid in DTI evaluation's segmentation and detection [18, 19]. In this study, we show how to implement a specific kind of CNN called a Convolutional Neural Network (CNN). Convolutional neural networks (CNNs) are widely used in machine vision applications. This is meant to mimic the way neurons in the brain communicate with one another. One input layer, several hidden layers, and one output layer make up the convolutional neural network. The network's robustness and resistance to overfitting are supported by the hidden layers, which consist of a convolutional layer, a pooling layer, an activation layer, and a fully connected layer. Fully linked layers are another kind of hidden layer. In the convolutional layer, a filter "convolutes," or iteratively traverses and analyzes the input image's pixel values. Colors, arcs, and boundaries may all be determined with the help of this array. After the first layer of processing is complete, a numerical activation map is produced. The output of the map is a set of numbers that stand for the presence or absence of certain visible features. The SoftMax layer is the last stage of a convolutional neural network (CNN) and is used to evaluate the relevance of the map of activation's high-valued attributes to a given picture classification. Until the training data yields consistent results, the thresholds and weights of the different layers are adjusted during the "training" process.

Darknet, an open-source implementation of the YOLO technique, may be used for image classification and object identification [23]. YOLO's architecture achieves both goals in a single pass, which not only speeds up detection but also increases mean average accuracy and reduces mistakes brought on by background noise [25]. Bounding boxes are a great tool for improving the effectiveness of this kind of item identification. The YOLO system utilizes a single convolutional neural network (CNN) to perform numerous tasks concurrently, such as calculating class probabilities and setting box borders [3]. In order to identify objects and pinpoint their locations, YOLO at the picture is used [6]. The substantially modified YOLO model outperforms state-of-the-art detection approaches on novel input images. Detector YOLO just needs one simple operation to complete bounding box regression and classification simultaneously. The object's category (such as Non, Very Mild, Mild, or Moderate Demented) is determined during the classification phase, and its location within the picture is determined during the regression phase using the box that surrounds it. The goal of the categorization phase is to pinpoint the precise location of the object in the images.

2. LITERATURE SURVEY

According to A. Kahn et.al. [1] describes an challenging to detect and predict the progression of Alzheimer's disease from the early stage of Mild Cognitive Impairment (MCI). Citing: Khan et al. Regression analysis is a statistical method for determining which characteristics and indicators are most strongly correlated with a desired result. The major goal of this study is to use a total of 20 different biomarkers in combination with medical information to conduct a tailored regression analysis of cognitively typical persons and MCI converters. From a total of 1713 male and female participants, 768 female respondents were chosen to examine the prevalence of AD and MCI, the characteristics of individuals diagnosed with AD and MCI, and the variables that contribute to their development. The data utilized in this study came from the Alzheimer's Disease Neuroimaging Initiative (ADNI). Twenty different potential medical characteristics were included in the analysis. Factors from a wide variety of diagnostic procedures, including MRI, PET, DTI, and EEG, were included in this analysis. The results indicated that cognitive assessment measures were much more important than other testing biomarkers. The results of this research may have implications in the clinical setting, either by helping to refine a machine learning approach to predicting the progression from MCI to AD or by helping to identify key people for therapy trials.

J.'s study aimed to determine. K. Medina et al. [2] aims to create a system that can consistently diagnose fish infections far earlier than the conventional method. The device uses a camera component to capture still images or stream video of goldfish, which are then pre-processed to bring out their most salient features. The YOLO method extracts characteristics after they have been segmented. Following that, the technique categorizes each identified disorder. The collected data successfully identified and classified the goldfish specimens with a 91% overall detection rate. Using CNN and YOLO, this inquiry helped solve the problem by identifying the most common sickness among goldfish. This instrument is useful for the early diagnosis of illness and may be used by both novice fish producers and veterinary technicians or aquarium owners.

W. The YOLO v5 technique is used by Fan et al. [3] to diagnose 14 lung illnesses through abnormal target detection in chest X-rays. The primary goal of developing this method was to aid in the diagnosis of lung ailments. The Vindr-CXR dataset made public by the Kaggle Competition was used to verify the accuracy of the YOLO version5 anomaly detection system. Experiment results show that the YOLO v5 strategy, used in this study, is more accurate than competing approaches when it comes to spotting outliers. When compared to the Faster RCNN and EfficientDet methods, the metric score is 7.2% higher. This offers as evidence that the method is effective in picking out abnormalities in chest X-rays.

M. Hashim et al. [4] present a state-of-the-art, extremely effective method for diagnosing agricultural diseases. The proposed method will employ the YOLO approach to identify plant diseases. Compared to other object recognition methods, the YOLO algorithm can analyze 45 frames per second in rapid succession, making it ideal for analyzing photographs of leaves. Segmenting the picture into a grid of cells is the initial step in image analysis. One neural network can predict both the box sizes and the class probabilities in a single assessment. The offered technology will assist farmers in early disease detection, leaf disease identification, and crop management to guarantee the safety and health of plants.

A. According to Morbekar et al. [5], India is home to billions of smallholder farmers who rely on farming as their main source of income. The possibilities accessible to farmers for selecting profitable crops are vast. Farmers, however, remain in the dark about numerous diseases that might affect their crops because of a dearth of relevant information. When harvesting sick crops, many farmers have trouble and waste a lot of time. Timely analysis of the situation is crucial for avoiding costly consequences and maximizing output. The proposed system employs the YOLO technique as a novel application of the object detection approach for disease diagnosis in plants. In comparison to other technologies, YOLO's real-time processing of 45 frames per second is much faster when applied to images of leaves. The picture must be divided into several grid cells before further processing can begin. The prediction intervals and class probabilities are all calculated using a single neural network. This improves the speed and accuracy with which leaf diseases may be diagnosed.

"Y" claims. Chest pain is one of the most common medical complaints, according to research by Yuan et al. [6]. Chest X-rays play a crucial role in the evaluation and diagnosis of chest illnesses. Artificial intelligence applied to X-ray images may provide a workable answer to the shortage of healthcare resources and the heavy burden imposed on clinicians. This research looks at the feasibility of using the real-time detection technique YOLOv4 to 256-level grayscale pictures, which does not provide enough information for precise diagnosis. Therefore, a method is created to transform black-and-white X-ray images into those that seem to have color. Grayscale X-ray pictures, which only provide a minimal amount of information, are converted to color X-ray images, which reveal much more detail. The YOLOv4 is then put through its paces by being taught to identify the chest X-ray's colorful pictures. Publicly accessible datasets are used to evaluate the method, and the results of the trials show that the method can accurately detect and locate chest X-ray problems.

A. Mohandas et al. [7] provide an algorithm that can identify and recognize the plant illnesses that damage the leaves by using techniques often connected with the identification of objects in Image Processing. The Yolo v4 architecture, which is based on convolutional neural networks (CNNs), is used to do real-time object identification. Tomatoes, mangoes, strawberries, beans, and potatoes are just few of the plants whose leaves are the subject of this study. Bacterial and fungal diseases, as well as blight, are major causes of leaf damage in plants. One probable cause of these conditions is exposure to biological agents, sometimes called pathogens. The focus of this study is on recognizing and identifying illnesses of plant leaves using a specific model called YOLOv4-tiny in order to provide a preventative approach against the related ailment. The approach culminated in the system's incorporation into an android-based application. Users of this app would have a direct line to a diagnostic service for leaf diseases in real time.

S. made use of the revelation of the image-immortalizing YOLO c4 object. A reaction that helps generate more public interest in and support for covering up in public is highlighted by Degadwala et al. [8]. Good coding constraints are already included into the given Yolo v4 learning model. Even when they can't fix accuracy problems or meet complex arrangement demands, the company nonetheless promises fast access that may provide satisfying results. The suggested strategy might be divided into three parts: exposed skin, no cover, and no disguise. Because of how well it performed throughout development and testing, the model achieved a degree of accuracy of 99%, which was more than that of any of the alternatives considered.

K. In order to automatically recognize cysts in ultrasound images, Mahajan et al. [9] suggested a novel and extremely effective method. The YOLO approach was developed in this work to automatically identify PCOS and non-PCOS images in real time. The proposed method uses a single Convolutional Neural Network to automatically identify ultrasound images with PCOS and those without.

The Y might vary from the YOLOv5 perspective. In order to identify and categorize COVID-19, Li et al. [10] provide a method. The results of the studies show that the algorithm's efficacy is higher than that of other deep learning algorithms. More specifically, compared to the Fast RCNN technique and the Efficient Net design, the forecasting output has a map index (0.5) of 0.605, an increase of 32% and 18% respectively.

A. Koirala et al. [11] propose a novel approach to improving the performance of deep learning algorithms for the purpose of recognizing infections on microscope photos of thick blood smears via the consistent labeling of ground truth bounding boxes. The ground truth labels may be applied consistently to the bounding box to achieve this. Recommendations are made based on the outcomes of reliability and reproducibility tests conducted on the trained models. To maximize efficiency in terms of accuracy and speed of detection with minimal resources, a custom deep learning framework called YOLO-mp was developed. Specially developed 3-layered and 4-layered,YOLO-mp-3l and YOLO-mp-4l models achieved best mAP ratings of 93 (@IoU=0.5) and 94 (@IoU=0.5), respectively, for identification of the parasitic infections pathogen on a publicly available set of thick blood smear microscope pictures obtained with a phone camera. It has been shown that YOLO-mp-3l (with BFLOPs and model size equal to 21 and 24Mb) and YOLO-mp-4l (with BFLOPs and model size equal to 24 and 25 Mb) are superior to regular YOLOv4 (with BFLOPs and model size equal to 127 and 244Mb) when it comes to the amount of memory and processing power they require.

Because to A's efforts, ophthalmologists can now detect diabetic retinopathy at any stage. Padyana et al. [12], which aims to classify diabetic retinopathy into its various stages. The proposed method employs YOLO-RF to classify the picture data into several groups. Support vector machine, Decision Tree, Random Forest, and YOLO were among the traditional machine learning classification techniques compared with the proposed approach. Retinal fundus pictures from KAGGLE and IDRID were used for this analysis. With an accuracy of 99.3%, precision of 97.2%, and recall of 99.1%, the results show that the YOLO-RF model proposed for the system performed brilliantly.

According to M., Alzheimer's disease is a degenerative brain ailment that irreversibly erodes mental faculties over time. Authors: Velazquez et al. Recent years have seen extensive research on the link between the prodromal stage of MCI and the development of Alzheimer's disease, with the hope of finding a method to make an early diagnosis of the illness. Early detection at the MCI stage may select appropriate therapy measures and help to research study enrollment since 32% of persons with MCI will be diagnosed with Alzheimer's disease over the following five years. Researchers have shown encouraging results when classifying Alzheimer's disease stages using machine vision in combination with MRI, DTI, and PET. DTI-centric research has shown that there are substantial differences in white matter organization throughout different developmental phases. In order to identify the 32% of people with Early MCI who would eventually develop Alzheimer's disease, an alternative to phase classification is proposed: a recurrent neural network model (RNN) dependent on the DTI modality. The study's results are state-of-the-art because they show how accurately certain individuals' likelihood of receiving an Alzheimer's diagnosis over the next 5-7 years may be predicted.

In A.'s opinion. According to Thushara et al. [14], Alzheimer's disease is a global epidemic that affects millions of people's brains. Individuals and their loved ones face a dramatic drop in quality of life as a consequence of the disease. Since Alzheimer's is only diagnosed in its advanced stages, the only treatments available are palliative. There are currently no drugs available that may slow or halt the disease's progression. Therefore, the most efficient method for developing a treatment strategy is an early diagnosis of Alzheimer's disease. Neuroimaging techniques such as magnetic resonance imaging (MRI), diffusion tensor imaging (DTI), positron emission tomography (PET), and resting-state functional magnetic resonance imaging (rs-fMRI) may detect the structural and functional changes brought on by Alzheimer's disease. In recent years, machine learning methods have gained traction for use in analyzing neuroimaging data acquired by MRI imaging techniques for the goal of identifying and prognosing neurological diseases. In order to classify and make predictions about Alzheimer's disease, a random forests-based classification method is used in this research. The TADPOLE data collection, used in this study, was made available to the researchers by the Alzheimer's neuroimaging Initiative (ADNI). This study's multiclass strategy for determining AD stages has achieved accuracy on par with that of current studies in the area of Alzheimer's prognosis.

Findings by K. Diffusion tensor imaging, as described by Aderghal et al. [15], is an emerging imaging method that supplements structural MRI data in studies of Alzheimer's disease. Recent studies looking into the pathologic stages of Alzheimer's disease have relied heavily on Mean Diffusivity maps, which are obtained using the Diffusion Tensor Imaging modality. Deep Neural Networks are appealing tools for the classification of imaging data from people with AD, which is a key component of computer-assisted diagnosis. The main problem is that there isn't a publicly accessible database that has sufficient amounts of training data for both paradigms to solve the problem. Over-fitting occurs when there aren't enough data to properly train a model. We offer a learning strategy that is portable across modalities, in this case from structural MRI to DTI. In order to train on Mean Diffusivity data, models developed from a structural MRI dataset with domain-dependent data augmentation are used to activate network variables. With this method, overfitting is mitigated, learning efficiency is increased, and prediction accuracy is improved. A portion of the ADNI dataset is classified better between healthy controls, Alzheimer's patients, and persons with mild cognitive impairment once the classification algorithms are merged using a majority vote.

Normal cognition, mild cognitive impairment (MCI), moderate to severe MCI, and Alzheimer's disease are the four classifications used when A. For AD spectrum individuals, Song et al. [16] implement and assess a multi-class GCNN classifier for network-based classification. These people are divided up into four categories. Using structural connection graphs produced from DTI findings, the network architecture is designed and validated. Using receiver efficiency curves, we show that the GCNN classifier outperforms a support vector machine classification model by margins that vary depending on the kind of illness being analyzed. The findings show that the performance gap between the two methods widens as the disease develops from CN to AD. This shows that GCNN may be used to effectively stage and categorize patients throughout the AD spectrum.

X. An entirely novel strategy for assessing AD is proposed by Guo et al. [17]. In order to examine the characteristics of the whole brain, a network of the brain was built from scratch using an original segmentation atlas, and global graph conceptual variables were calculated. Using this comprehensive map of the brain, we may then get the graph theoretical characteristics of specific brain regions. Finally, neuropsychology measures are employed to conduct a correlation study between the conceptual properties of the graph and scale scores in various subdomains. The results not only emphasize the correlation between neuroimaging data and neuropsychological assessments, but also offer strong evidence for the relationship between medical outcomes and physiologic brain lesions of people with AD [20].

3. PROPOSED SYSTEM

The input to the system will consist of MRI or PET images that have undergone pre-processing. This imaging method utilizes radio waves and magnetic fields to generate high-fidelity, high-resolution two-dimensional (2D) and three-dimensional (3D) pictures of specific areas inside the brain. X-rays and radioactive tracers are not associated with the production of any harmful radiation. The structural magnetic resonance imaging (MRI) modality is often used to evaluate brain volumes in vivo with the aim of detecting brain degeneration, making it the most frequently utilized MRI technique in instances of Alzheimer's disease (AD). The Positron Emission Tomography (PET) imaging procedure involves the use of radiotracers to see the brain's activity as radioactive spheres. Data augmentation is a technique used to generate more training data by intentionally manipulating current data. Transformations include various operations such as shifts, flips, zooms, and other manipulations often used in the realm of image editing. In general, picture data augmentation is often applied just to the training dataset, while the validation and test datasets remain unaltered. The primary aim of image segmentation is to effectively cluster regions within an image that have common characteristics and can be classified as belonging to the same object class. This method is sometimes referred to as pixel-level categorization. In other words, this process involves the partitioning of images (or frames of video) into many segments or distinct entities. Ultimately, the act of reducing the amount of data facilitates the machine's ability to construct a model with less exertion, hence expediting the processes of machine learning and generalization.

A pre-existing model refers to a model that has undergone prior training to effectively tackle a comparable challenge. One approach involves using a pre-trained model that has been previously trained on a different issue, as opposed to commencing the problem-solving process from the beginning when faced with a comparable challenge. A convolutional neural network (CNN) is a class of deep neural networks that is specifically designed for the purpose of analyzing visual images within the context of deep learning. Subsequently, the obtained data will be subjected to analysis, enabling the formulation of suitable preventive dietary plans, exercise regimens, and other pertinent advice aimed at mitigating further complications.

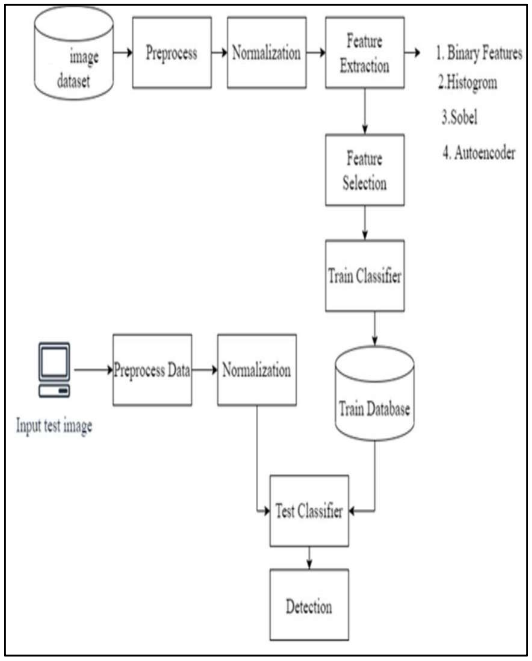

Figure 1 : proposed system architecture for Alzheimer disease detection and classification

CNNs are multiple encoders that have been specifically developed to recognize two-dimensional (2D) forms and may be used to transfer the input vector to the required output. Each neuron in a CNN is linked to a neuronal in a small region of the network's preceding layer, decreasing the number of weights in the network. CNNs utilize a hierarchical connection topology similar to conventional neural network models. A CNN, in other words, is made up of components that are layered layer by layer. Figure 1 shows convolutional, pooling, and fully linked layers, as well as an output layer. Convolutional and pooling layers alternating in these first few layers of a conventional CNN, succeeded by the fully - connected layers. The categorization results are generated by the final output layer. Finally, system demonstrates a Alzheimer detection class for entire test dataset.

4. RESULTS AND DISCUSSIONS

The accuracy of the Alzheimer detection algorithms can be measured through train and testing model. The i7 Intel processor has used with 16 GB RAM. The model has run with different methods such as RESNET-50, RESNET-100 and RESNET-101 with deep CNN. In below Table 1 and Figure 2 to 6 demonstrates proposed model evaluation and Figure 7 describes comparative analysis of proposed system.

Table 1: performance analysis of proposed model

Epoch size	Method	No. of hidden layers	Detection Accurac
20	RESNET-50	5	96.15
	RESNET-100	10	96.95
	RESNET-101	15	97.00
40	RESNET-50	5	96.45
	RESNET-100	10	97.60
	RESNET-101	15	98.50
60	RESNET-50	5	97.10
	RESNET-100	10	97.80
	RESNET-101	15	98.55
80	RESNET-50	5	97.4
	RESNET-100	10	98.30
	RESNET-101	15	98.95
100	RESNET-50	5	97.95
	RESNET-100	10	98.40
	RESNET-101	15	99.35

Table 1 provides a description of three distinct deep learning modules of RESNET, each with frameworks consisting of 50, 100, and 100 layers respectively. The study demonstrates that increasing the number of hidden layers results in an increase in time required and also improves the accuracy of the module.

The ResNet, is Residual Networks, is a specific form of deep neural network structure that was developed to tackle the issue of the vanishing gradient problem in networks with a large number of layers. The primary advancement of ResNet lies in the incorporation of residual blocks, which consist of skip connections or shortcuts that allow for bypassing certain levels. This facilitates the training of more complex networks by enabling a smoother flow of gradients across the network.

5. CONCLUSION

The purpose of this study was to apply the popular YOLOv4 and YOLOv8 algorithms to the task of multiclass classification, specifically in the context of brain DTI scans taken from persons with Alzheimer's disease. These models could be implemented effectively, and the research that led to that conclusion added considerable new information to the area of medical imaging. The study has provided valuable insight into the use of machine learning in medical imaging diagnosis, expanding the scope of possible future studies. Radiologists may employ technique predictions, like as those produced by

5 10 15 97.95 98.4 99.35 0 20 40 60 80 100 120 RESNET-50 RESNET-100 RESNET-101 No. of hidden layers Detection Accuracy

97.95 98.4 99.35 97 97.5 98 98.5 99 99.5 VGG [8] ShallowNet [10] RESNET-101

YOLOv8, to supplement their in-depth knowledge of Alzheimer's disease patients' medical conditions. The described models may be improved upon by adjusting the parameters of the YOLOv4 and YOLOv8 algorithms and doing performance optimization. This requires more time spent training the models, better image enhancement for better image recognition, and the creation of more images to help smooth out inequalities in the training dataset. The next phase of the study will include the categorization of ensembles via the use of a "voting ensemble," in which the most popular prediction will be implemented. The main advantage of utilizing an ensemble classification model is that a classifier using ensembles may correct mistakes produced by individual classification models and combine the results of several classification models to obtain the best achievable accuracy.

6. Limitations and Research Gaps

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7. Conclusion

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