Machine Learning Model for Evaluative Performance of Medical Images Using Classifiers

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Abstract: Computer Aided Diagnosis is becoming popular in medical sciences as it provides accuracy and timeliness, the two major aims of medical field. In the work presented here, an algorithm is developed which aims to design an auto-CAD system for the diagnosis of retina abnormalities. Diabetic Retinopathy becomes severe if not diagnosed and treated at the first stage. Age-related Macular Degeneration is another vision threatening disease that occurs in the elderly population and needs serious medical attention. In this research work, these two diseases are considered and the signs of these two diseases are analyzed. A combined database is formed by collecting the images from several standard datasets. The algorithm presented in this work is developed with the combination of two steps, namely, image processing and machine learning. Several image processing algorithms for segmentation and morphological operations are used for the detection of the abnormalities caused by the above mentioned diseases. A set of significant features are selected and evaluated on the abnormalities extracted in the image processing stage. The classification of the abnormalities with a training and a test set is performed using different machine learning algorithms. The random forest classifier is best suited to the dataset used in this research for its performance accuracy and robustness with respect to noise. With the aim of forming a Case Based Reasoning model, we have developed a method of machine learning based classification of different abnormalities

***Keywords:** Computer Aided Diagnosis, Retina Abnormalities, Diabetic Retinopathy, Age-related Macular Degeneration, Image Processing, Machine Learning, Segmentation, Morphological Operations*

Introduction

When it comes to diagnosing, treating, and keeping tabs on a wide range of medical diseases, medical imaging is essential because of the deep insights it provides into the human body. There are advantages and disadvantages to effectively analysing and interpreting the massive volumes of medical picture data produced every day by digital imaging technology[1][2]. Manual interpretation by radiologists is a common component of traditional image analysis systems; however, this process may be laborious, subjective, and error-prone. Computer algorithms are used to process digital photographs in order to classify them. In any image processing task, the three main components are the image capture device, the picture analysis, and the output of results[3][4][5]. By applying various operations to an input picture, useful information may be extracted or the image can be enhanced. Image processing encompasses a wide range of subjects, including but not limited to: pattern recognition, image editing, segmentation, restoration, feature extraction, classification, and multi-scale image analysis[6].

An essential aspect of image processing is the classification and labelling of groups of pixels or vectors within an image based on established criteria. Selecting training data from images and assigning it to predefined classes is essential for supervised image classification to function[7]. Deep learning is a crucial area of machine learning that relies on ANNs, which are hierarchical structures that may include several algorithms[8].

A biological neural network similar to that of the human brain might one day replace ANN. When working with massive datasets, deep learning algorithms often outperform their more traditional alternatives [1].

Machine learning (ML) approaches have arisen as potent instruments for automating and improving medical image processing in response to these difficulties[9]. Machine learning algorithms are able to efficiently and accurately analyse images automatically by learning characteristics and patterns from massive datasets. The use of classifiers, a subset of ML models, to evaluate and classify medical pictures according to established standards has particularly shown encouraging results[10].

The purpose of this research is to investigate medical picture evaluation using machine learning classifiers. Our discussion will centre on the importance of this field of study, our evaluation of current methods and procedures, and our suggestions for future research directions[11].

Significance of the Research:The evaluative performance of medical images is critical for accurate diagnosis, treatment planning, and patient management across various medical disciplines, including radiology, pathology, and dermatology. Traditionally, this process has relied on human expertise, which can be limited by factors such as inter-observer variability, fatigue, and time constraints[13][14]. By leveraging machine learning classifiers, we can enhance the efficiency, consistency, and accuracy of image evaluation, leading to improved patient outcomes and healthcare delivery[15].

Furthermore, the growing availability of digital imaging archives presents an opportunity to leverage this wealth of data for training and validating machine learning models. By harnessing the power of big data analytics, we can develop classifiers capable of detecting subtle patterns and abnormalities in medical images that may evade human perception[16].

Existing Methodologies and Techniques A wide range of machine learning algorithms have been applied to the evaluative performance of medical images, including but not limited to:

Convolutional Neural Networks (CNNs): CNNs have demonstrated remarkable success in image classification tasks by automatically learning hierarchical features from raw pixel data. They have been extensively used for tasks such as tumor detection in radiology images, cell classification in pathology slides, and lesion segmentation in dermatology images.

Data Quality and Quantity: Access to high-quality annotated medical image datasets remains a bottleneck for training robust machine learning models. Collaborative efforts are needed to curate large-scale datasets with diverse patient populations and imaging modalities to improve model generalization and performance[17].

Transfer Learning and Domain Adaptation: Leveraging transfer learning and domain adaptation techniques can facilitate the transfer of knowledge from related tasks or domains to target medical imaging applications with limited labeled data. This approach can help overcome data scarcity issues and accelerate model development[18].

Integrating and Validating for Clinical Use: To evaluate the clinical value and effect on patient care, it is essential to validate the performance of machine learning classifiers in actual clinical contexts. Simplifying validation and integration requires partnerships between regulatory agencies, healthcare providers, and machine learning researchers[19][20]. Due to its effectiveness and precision in detecting anomalies caused by various illnesses, computer-aided diagnosis (CAD) is gaining popularity in the medical sciences. The medical profession also benefits from the timeliness of computer-aided design based solutions[21]. One reason CAD systems are so popular is their ability to give service nonstop. More and more, CAD solutions are being developed with the express purpose of assisting doctors. In order to create a CAD system, this study lays forth methods to identify and categorise retinal defects. These approaches rely heavily on machine learning and image processing phases. This study takes into account the retinal anomalies caused by age-related macular degeneration (AMD) and diabetic retinopathy (DR). Experts in eye care say that if left untreated, the aforementioned conditions are rapidly becoming the leading causes of irreversible blindness. It is difficult to manually recognise the early symptoms of these disorders[22]. This is why the researchers focused on these two disorders. One of the main parts of the method that this article presents is image processing. Automatic abnormality detection in retinal pictures caused by AMD and DR is achieved via a series of image processing procedures. Crucial to this issue is image segmentation. Various image segmentation techniques are examined and their efficacy is evaluated using the retina image database used in this study.The machine learning stage is also crucial to this project[23]. This work examine the retinal pictures that have been treated using various image processing methods. In order to identify anomalous items, we first create a collection of important characteristics and then assess the feature values. There is a training set and a test set for the feature vector[24]. At this stage, we evaluate the efficacy of several machine learning methods.

The need for imaging techniques such nuclear medicine, PET, endoscopy, CT, MRI, MRA, and pathological diagnostics has skyrocketed in the healthcare system. In addition, medical image processing is a time-consuming and sometimes challenging process due to the acute shortage of radiologists[25].

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 12
***Article Received:** 25 July 2022 **Revised:** 12 September 2022 **Accepted:** 30 November 2022*

The use of AI has the potential to address these concerns. Computers can learn from data and derive conclusions or predictions based on that data without human involvement thanks to machine learning (ML), a field of artificial intelligence. In machine learning, supervised, unsupervised, and semi-supervised learning are the three primary approaches. A domain expert is required to choose the most relevant features for a certain scenario while using feature extraction, one of the ML techniques. Use deep learning (DL) techniques if you need to choose features. Deep learning (DL) is a subfield of machine learning that can automatically identify important features in raw input data [25]. The original domains where DL algorithms first appeared were cognitive science and information theory. First, DL is characterised by its capacity for various processing layers to learn various data features at different abstraction levels. Second, each layer may learn to display information either unsupervisedly or with some amount of supervision. Several recent review articles have highlighted the medical applications of advanced DLA. Research in the fields of magnetic resonance imaging (MRI) [8], radiology (96), cardiology (11), and neurology (12) falls under this category.

The primary goal of this study is to provide doctors with better tools for the early and precise diagnosis of retinal anomalies caused by DR and AMD. This study develops an approach that may be used to a CAD system for the automated detection of retinal defects. When compared to manual identification, the use of a computer-aided design (CAD) system simplifies the process of identifying and classifying lesions from retina images. The suggested solution may alleviate some of the burden on an eye specialist's duties. We use image processing processes to analyse input retina pictures and identify any anomalies. We next check the discovered esions using a set of feature values. In order to categorise the identified lesions from the image processing stage, the machine learning procedure is executed. Because the human eye has a hard time distinguishing between subtle colour changes, manual identification may be inaccurate. The tedious procedure of anomaly detection from the retina picture is another reason for the decreased accuracy. When working with a retinal picture, several factors may influence the diagnosis. These kinds of problems can be solved using the suggested approach. Eye doctors may benefit from the suggested methodology's efficiency and accuracy in the diagnosis and categorization of retinal disorders.

Famous databases such as DiaretDB0 [1], DiaretDB1 [2], e-ophtha [3], and Messidor [4] provided the retina pictures used in this study. Images of the retina showing various forms of DR are included in these databases. The dataset includes the original, unaltered version of every photograph. Additionally, some typical retinal pictures are gathered. Pictures of AMD-afflicted retinas are culled from online resources.

The retina is linked to many layers of neurons. Vision in dim light is produced by the retina's rod cells, whereas vision in bright light is produced by the retina's cone cells. These cells, called photoreceptors, are able to take in light and transform it into messages that the brain can use. With this condition, the optic nerve is damaged and the retina is unable to transmit neural impulses to the brain. Rapid onset of AMD might cause irreversible vision loss. As AMD progresses, a hazy region close to the macula develops. As time goes on, the afflicted individual may notice that their core vision is more obscured by this hazy region.

Memory loss in AMD progresses via three distinct phases. In the early phases of age-related macular degeneration, tiny to medium-sized drusen—yellow deposits—below the retina are present. At the beginning, there is no noticeable blurring of vision. Forming at an intermediate stage of AMD are huge drusen. Even though many individuals are oblivious to the fact that their eyesight is changing, little vision loss is still possible at this point. The last AMD stage is further subdivided into the wet and dry AMD stages. Damage to the macula's light-sensitive cells leads to dry age-related macular degeneration (AMD), which in turn causes vision loss because the damaged cells can no longer send visual signals to the brain.

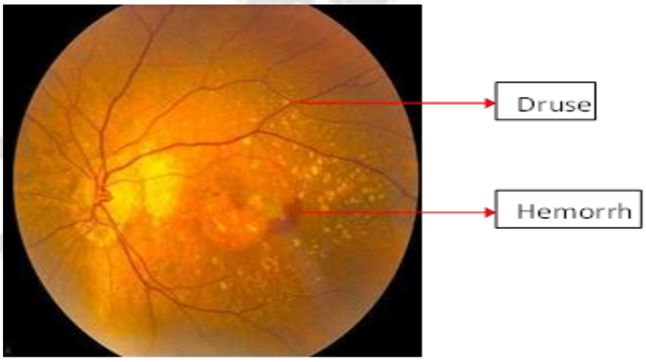

Figure 1: Different signs of Age related Macular Degeneration

The basic algorithm followed in this research work

There are two main parts to the research process: processing images and learning how to interpret them. Using the conventional databases, a database of retinal pictures

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 12
Article Received: *25 July 2022* ***Revised:*** *12 September 2022* ***Accepted:*** *30 November 2022*

impacted by AMD and DR is built in the image processing stage. These pictures are considered input. In order to make the input photographs better, they are pre-processed. After then, segmentation is carried out in order to identify clusters of light and dark pixels. In order to identify foreign objects, procedures such as removing the optic disc (OD) and the blood vascular tree are used. Each anomalous item undergoes examination of a set of feature values throughout the machine learning phase. A collection of feature values including all the identified lesions is produced by this. Separated from this collection is the data used for training and testing. The next step is to use the training data to train the machine learning classifier. The accuracy of the machine learning classifier is assessed using a test set after its training. Weka, a data mining programme, was used for the machine learning step in our study [10].

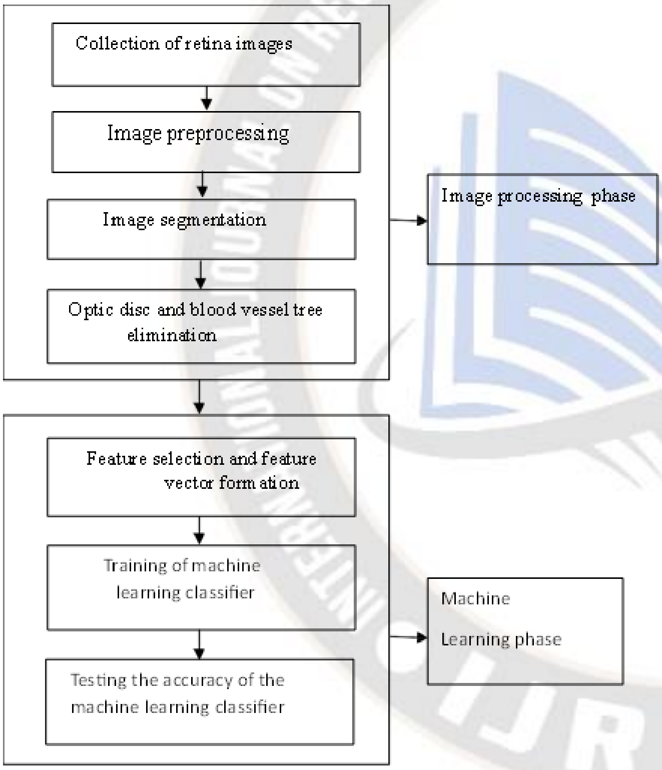

Figure 2.: Graphical representation of the proposed methodology

A significant component of the progress in medical sciences is the new work in CAD systems. Our goal is to help ophthalmologists see signs of DR and AMD earlier in their patients. In order to create a computer-aided detection (CAD) system for abnormality identification in retina pictures, key characteristics are retrieved from input images utilising suitable image processing techniques, feature selection, and machine learning approaches. Several methods for image processing and machine learning form the basis of the proposed technique in the study effort. The input database consists of a collection of around 400 retinal pictures that have been impacted by AMD and DR. We are pleased with the outcomes of the DR and AMD symptom identification and categorization processes. Natural picture recognition in computer vision and other difficult machine learning problems have been solved with the help of large annotated datasets that could include millions of photographs. So, many are hoping that similar breakthroughs will happen in medical applications and that algorithm research will eventually provide a solution to the discriminating problem, a clinical difficulty. Contrarily, healthcare datasets are often much smaller, with hundreds to thousands of records: herewith a collection of sixteen "large open source medical imaging datasets" ranging in size from 267 to 65,000 patients. Although we are discussing medical imaging themes, it is conceivable for a same subject to be photographed several times or in different places. For simplicity's sake, we will pretend this is a diagnostic task requiring just a single image or scan per person.

Important aspects emphasised in the study must be considered in order to provide a machine learning model for assessing the classifier performance of medical pictures. When it comes to healthcare clinical decision support systems, machine learning classifiers—whether they're using shallow or deep learning—are essential.

Task, dataset, explainability criteria, and computer resources are the factors that determine the method choice.

Accuracy, precision, recall, F1-score, and confusion matrix are popular metrics used to measure model performance in medical image categorization.

In contrast to accuracy, which is defined as the proportion of properly categorised pictures, precision refers to the proportion of correctly anticipated positives and recall to the proportion of correctly predicted real positives.

The F1-score provides a fair assessment of the model's performance by integrating recall and accuracy into one statistic.

Because of their discriminating character, few clinical concerns can be simply articulated as machine-learning problems. But even with them, the expected benefits of using larger datasets have failed to materialise. For example, with an ageing population comes a higher chance of health problems, such as Alzheimer's disease (AD), making early identification of AD more vital. With an early diagnosis, therapies have a better chance of being effective when implemented early on. Numerous efforts have been made to acquire large brain-imaging cohorts of potentially Alzheimer's disease (AD)-stricken older adults in order to find early biomarkers for AD. This has resulted in a rise in the typical number of people taking part in studies that develop computer-aided diagnostic tools for AD (or its predecessor, mild cognitive impairment) using machine learning.

Common Machine Learning Classifiers Used In Medical Image Analysis

Common machine learning classifiers used in medical image analysis include traditional machine learning algorithms like support vector machines (SVM), random forest, and XGBoost, as well as deep learning architectures such as convolutional neural networks (CNNs) and vision transformers

These classifiers play a vital role in developing clinical decision support systems in healthcare by providing insights for tasks like disease detection, classification, and treatment response assessment

The choice of classifier depends on factors like the task, dataset, explain ability requirements, and available computing resources, with considerations for task analysis, dataset size, and the need for interpretability guiding the selection process

Reasoning in the Detection of Retinal Abnormalities using Decision trees

Our research work was started to build an automatic system to detect and classify retina abnormalities due to DR and AMD. A Case Based Reasoning (CBR) was intended to develop though not fully implemented in the work titled “Case Based Reasoning in the Detection of Retinal Abnormalities using Decision trees”. The abnormalities of the retina were detected through image processing steps. A decision tree based model was proposed for classification but not implemented.

This work aimed to develop a model with decision tree for providing the decision support system in the detection of retina abnormalities. The study of previous works revealed that DR and AMD were dealt together in fewer works. As some of the signs of DR and AMD are similar in appearance, we wanted to consider both cases together.

Implementation Details

In the proposed method, contextual information obtained from the report of postprandial blood glucose (PPBG) examination is combined with the retinal images having abnormalities. A decision tree is used in this work. The proposed methodology of this work consists of three parts:

1. Collection of retina images with AMD and DR

2. Separating AMD from DR using decision tree

3. Detection of abnormal portion of retina If the patient’s PPBG is greater than one hundred and eighty, then the patient’s retinal abnormality should be treated as DR; otherwise, it should be treated as AMD. The detection of abnormal portions of the retina due to DR or AMD is dependent on image processing techniques.

The colored retinal image (input image) is converted to grayscale and then contrast enhancement is done on it. The processed image is then segmented into three clusters using the fuzzy C means clustering technique.

In this case, the cluster number is set to three because the retina image contains mainly three colors: bright yellow for the optic disc, dark red for blood vessels, and light red for the rest of the retina which includes membrane and plasma. From the segmented image, extraction of the cluster corresponding to the darkest region and the cluster corresponding to the brightest region is done separately. In the case of DR, the cluster corresponding to the darker region contains micro aneurysms or hemorrhages. In the case of wet AMD, the dark region contains blood clots. The cluster corresponding to the bright region contains hard exudates or cotton wool spots in case of DR and drusen in case of dry AMD.

Based on the provided sources, the conclusion regarding a machine learning model for evaluative performance of medical images using classifiers involves several key points:

Classifier Selection: The choice of classifier, whether traditional machine learning algorithms like support vector machines (SVM), random forest, and XGBoost, or deep learning architectures such as convolutional neural networks (CNNs) and vision transformers, depends on factors like the task, dataset, explain ability requirements, and available computing resources

Automated Analysis: Machine learning classifiers automate the analysis of medical images, enabling efficient processing of large datasets and reducing the burden on healthcare professionals

Accuracy and Disease Detection: These classifiers enhance disease detection accuracy in medical images, aiding in early diagnosis and treatment planning for conditions like breast cancer, cardiac diseases, and more

Quantitative Analysis: Machine learning classifiers facilitate quantitative analysis of medical images, allowing for precise measurements, disease progression tracking, and treatment response assessment by quantifying changes in images

Interpretability Challenges: While deep learning models like CNNs excel in feature extraction and classification, their black-box nature poses challenges in interpretability. Efforts are ongoing to develop techniques like attention mechanisms and saliency maps to provide insights into model decisions

In summary, the integration of machine learning classifiers, from traditional methods to deep learning architectures, offers valuable insights for evaluating the performance of medical images. By selecting appropriate metrics, benchmarking against baselines, and leveraging advanced models like CNNs with transfer learning, healthcare practitioners and researchers can enhance diagnostic accuracy and decision-making in medical imaging analysis

Conclusion

The integration of machine learning classifiers, ranging from traditional methods to deep learning architectures, offers valuable insights for evaluating the performance of medical images. By selecting appropriate metrics, benchmarking against baselines, and leveraging advanced models like CNNs with transfer learning, healthcare practitioners and researchers can enhance diagnostic accuracy and decision-making in medical imaging analysis. It is efficient in classification even if the dataset is not linearly separable. Our dataset contains the information about several lesions which are similar in many aspects (like hard exudates of DR and drusens of AMD are similar in color, size; haemorrhages of DR and blood clots of wet AMD are similar in color, shape)

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