Automated Medical Image Classification for Disease Prognosis

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Abstract. An interesting exploration challenge for computer vision experimenters is the automated classification of medical pictures, made possible by recent advances in imaging technology. Medical pictures need to be sorted into their proper categories, and a good classifier is essential for this. With our proposed approach, the system would be pre-trained to recognize and categorize medical pictures using deep learning techniques such as GoogLeNet, VGG-16 and ResNet-50 these three pre-trained deep convolutional neural networks are utilized for categorizing the different medical pictures. Using this picture bracketing approach to predict the appropriate category or sequence of unidentified photographs may be quite helpful. The findings of the experiment demonstrated with the standard dataset in which the proposed method is superior at categorizing different types of medical pictures.

Keywords: Medical Image Classification, Pretrained CNN, DCNN, ResNet-50.

1 INTRODUCTION

In recent years, the widespread integration of digital imaging in medicine has surged, driven by advances in camera technology and the prevalence of imaging equipment like CT and MRI scanners in modern health-care settings[1-3].These technologies, such as X-rays (electromagnetic waves), CT) scans, and PET scans, play a crucial role in aiding medical professionals in diagnosis and prognosis .However, the surge in the volume of digital medical images poses challenges in their efficient categorization, necessitating the development of classification algorithms.

The exponential growth in medical photographs has made manual classification laborious, prompting the exploration of data-driven approaches for improved efficiency.

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This shift focuses on creating algorithms that automatically label medical images depicting various biological systems. Leveraging machine learning, researchers aim to decode visual features such as color, form, position, and texture from images, facilitating the development of robust systems for accurate categorization [4-7]. Despite the challenges posed by diverse imaging modalities and diseases[8-10], recent strides in technology and methodology signal progress in narrowing the semantic gap and enhancing the capabilities.

2 LITERATURE SURVEY

The use of Convolutional Neural Networks (CNNs) and other cutting-edge methods has revolutionized medical image processing in recent studies. Merging three 2D convolutional neural networks (CNNs), synergistically enhances multidimensional data analysis and spatial feature extraction., is a common method for segmenting anatomical characteristics in medical imaging, allowing for classification at both the voxel and pixel levels. Using self-learning deep learning to improve VFR is a possible future direction [11-15]. Offers auto-OA-grading, a novel approach of evaluating x-rays to assess the severity of knee osteoarthritis (CNN). The Kellgren and Lawrence (KL) scale is used to quantify the discomfort and incapacity brought on by knee OA in clinical settings. In the past, attempts to automate KL grade prediction for radiological images made use of shallow classifiers trained on a broad variety of user-specified parameters.

After initial pre-training on ImageNet, improving the model with knee OA images may significantly improve the model's classification accuracy. The outcomes are enhanced if a regression issue is formulated to anticipate KL ratings. X-ray images dataset show performance gains above the state-of-the-art [16-19]. In many cases, cytopathology (or cellular pathology) is used to make a cancer diagnosis. Cytopathologists, a subset of pathologists, are crucial for the proper diagnosis and management of thyroid conditions. It is possible to generate images that stand out from the crowd and benefit pathologists in their investigations of disease and cellular structure. There is strong empirical support for the assertions stated for the method both quantitatively and qualitatively. Neuroimaging has shown promise in the past ten years for the detection of Alzheimer's Disease (AD), particularly in the prodromal stage of mild cognitive impairment (MCI).

A DBM is a type of deep network composed of restricted Boltzmann Machines. Next, we learn a combined of PET and MRI using a second DBM. Convolutional neural network (CNN) architecture is the method used by the Brain Net CNN to gather data. to predict clinical neurodevelopmental outcomes unlike existing CNNs, our Brain Net CNN does not rely on pictures to construct convolutions but rather on the topological locality of structural brain networks [20]. To predict how well children will do in school down the line, researchers have used the Brain Net CNN framework to a database of structural brain networks built from diffusion tensor imaging (DTI) scans of newborns. On this dataset, the Brain Net CNN architecture achieves better results than the state-of-the-art methods. When it comes to girls, Brain Net CNN can also accurately predict their first day of menstruation.

3 EXISTING SYSTEM

The extensive use of deep learning methods in computer vision has led to significant advancements in the categorization of medical images in recent years. Previous systems had problems due to their design, namely a lack of precision [21]. The usual categorization accuracy of these older methods was 85%, which was frequently insufficient. The use of shallow classifiers or traditional machine learning techniques was the main cause of their poor precision. Further, most prior systems depended significantly on human feature engineering, a time-consuming and domain-specific method that often hampered their generalizability across different types of medical imaging [22]. In addition, the lack of sufficient data from these earlier investigations prevented the creation of strong models.

In the previous setups, ensuring quality and preparing data were arduous chores. In addition, these preceding systems were often criticized for having difficulties with interpretability and generalization across different medical picture modalities [23]. They relied mostly on surface-level visual cues, which were inadequate for capturing the subtleties and complexities of medical imaging. Therefore, it was clear that the current systems were inadequate in terms of precision, efficiency, and responsiveness to changes in the healthcare industry [24-25]. As a result of these constraints, the proposed methodology was developed, which makes use of deep learning technologies like convolutional neural networks (CNNs) and transfer learning to improve upon the shortcomings of previous systems, resulting in an increase in classification accuracy to well over 90%.

4 PROPOSED METHODOLOGY

Disease prognosis is facilitated through the utilization of image classification datasets employing the proposed methodology. The combination of a convolutional neural network (CNN) and transfer learning using the ResNet-50 architecture attains a precision exceeding 90% across diverse datasets, enabling users to make dependable health forecasts. The anticipation of disease progression relies on recommended approach. Various preprocessing methods, encompassing augmentation, image filtering, transformations, and the utilization of CNN, ResNet-50, VGG-16, and transfer learning modules, contribute to achieving accuracy rates surpassing 90%. A large number of disturbing images exhibiting different anatomical interiors may be properly classified using this method. Because it may lead to more precise illness diagnosis and more effective treatment, the suggested model is of paramount relevance. With the goal of helping the doctor zero in on the cause of the problem and come up with a solution. Using convolutional neural networks and encoders may aid in medical picture classification. If the system determines that the picture is of a medical nature, it will continue with categorization and analysis, which may result in the identification of an image that is diagnostic of a disease, improving medical diagnosis and prognosis. For each of these actions, we need to create a method that has the potential to benefit the healthcare system. Using image classification datasets is key to the proposed method for illness predicting. Here we will investigate the use of deep learning by the categorization of medical pictures. To predict the incidence of disease, the proposed technique uses picture classification.

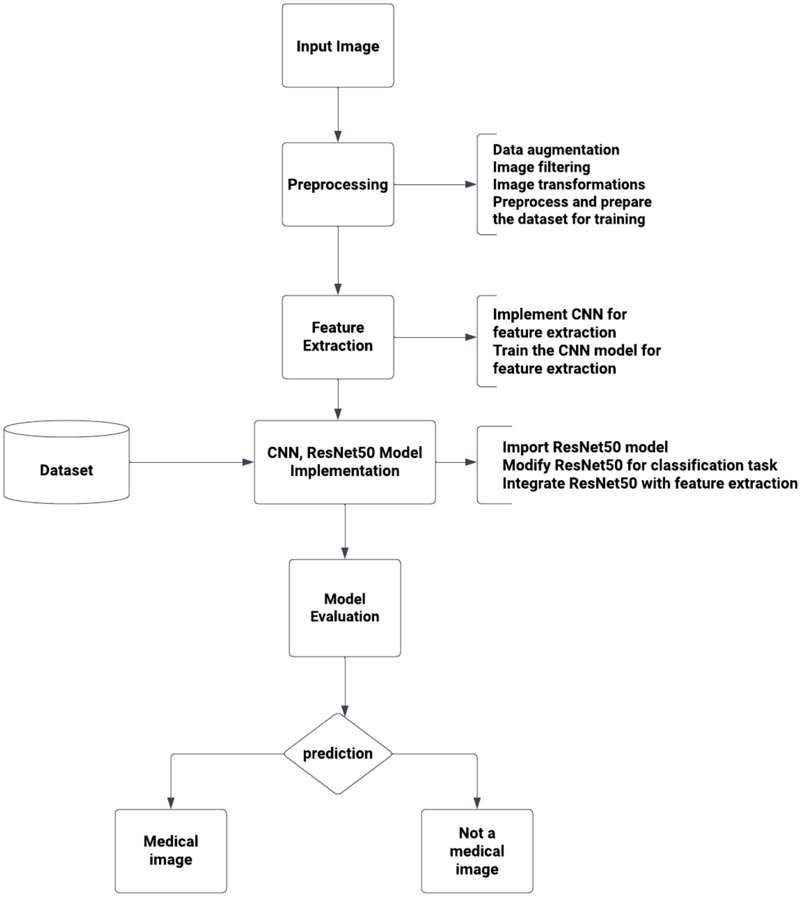

Fig. 1. System Architecture of proposed method

To achieve high-quality results, the system architecture initiates with the gathering of diverse medical image datasets, followed by meticulous preprocessing involving techniques like augmentation, filtration, and transformations. Subsequently, the model's predictive capability revolves around a specialized Convolutional Neural Network (CNN) utilized for effective feature extraction. The accuracy and general performance of the system is then improved by integrating and customizing the ResNet-50, VGG-16, GoogLeNet models for the given classification job. Standard metrics like accuracy, precision, recall, and F1-score are used to train and assess the combined model to determine its performance. The visual presentation and analysis of the data give useful insights into the categorization outcomes. In closing, it emphasizes the system's usefulness in the healthcare area due to its major contributions to precise illness prediction and diagnosis.

5 SYSTEM IMPLEMENTATION

Implementation of proposed system, CNN and ResNet-50 were employed.

a. CNN Algorithm

Procedural Steps

Input: Clinical Image Data

Output: Identification of disease and non-disease images requiring discernment.

Step-1: Initial steps include splitting the input dataset into test and training iterations.

Step-2: During the preparation of training data, for each image, calculate the pixel vector covariance based on its pixel dimensions. Identify the cluster of pixels with the highest correlation, designate it as the parent, and insert the pixels into the Content Tree as a child node. Create a Feature Map Content Hierarchy Node Group and feed it into a Convolutional Neural Network (CNN) to obtain relevant feature maps and sensitive information.

b. ResNet-50 Implementation

Step-1: This brings in the keras module and all its associated APIs. To aid in the development of the ResNet model's framework, these APIs are provided.

Step-2: Adjusting the necessary hyper settings.

Step-3: Identify the training rate based on the epochs. For more effective learning, the learning rate should be lowered as the number of epochs increases. In the context of ResNet design. In addition, our dataset was pre-processed so that it would be ready for training.

Step-4: The fundamental ResNet components that will be utilized to define the ResNet V1 and V2 architecture.

Step-5: Specify the ResNet architecture that will be used.

Step-6: Define the architecture of ResNet which utilizes the ResNet-50 component.

Step-7: The ResNet architecture contains training and testing code.

6 RESULTS AND DISCUSSIONS

This proposed work used Kaggle's repository of Brain MRI images for tumor detection. The Image Dataset was chosen above other available options because the grayscale pictures it includes are ideal for the training of our model. To provide a well-rounded dataset for the classification assignment. A training set of 70% of the photographs and a testing set of 30% of the photos were divided. This model performs much better than the previous model, which was only able to achieve approximately 90% accuracy on the same dataset.

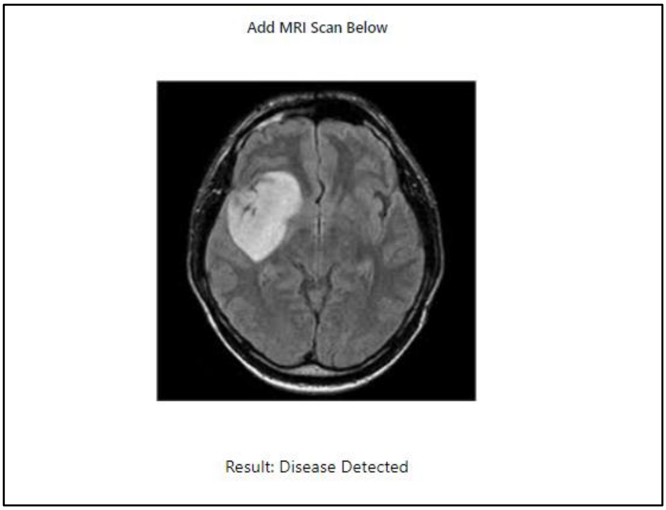

Fig2**:**Disease detected.

Fig 2 Represents the output of the medical picture detection process,showcasing the system's ability to correctly categorize an image as a medical picture

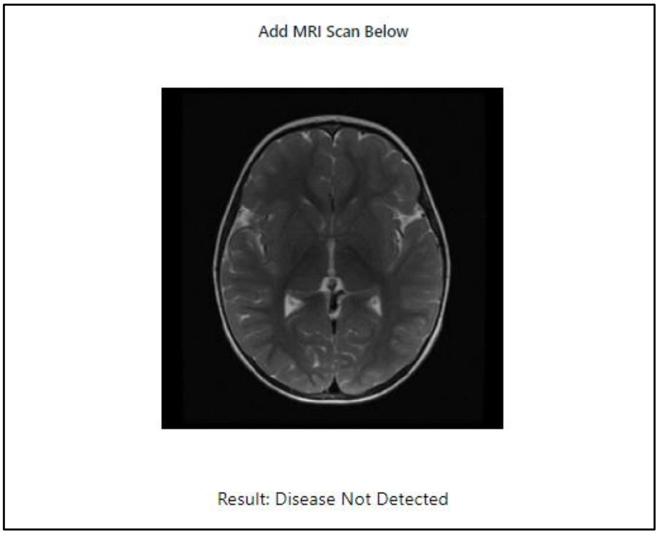

Fig3**:**Disease not detected.

Fig 3 Represents the result of running the medical picture identification algorithm, where a non-medical image is correctly identified as such.

This paper uses following formulas for calculating accuracy, precision, and F1-score.

$$Precision = \frac{TP}{(TP + FP)}$$

$$Recall = \frac{TP}{TP + FN}$$

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

Where , TN is True Negative , TP is True Positive, FN is False Negative, FP is False Positive.

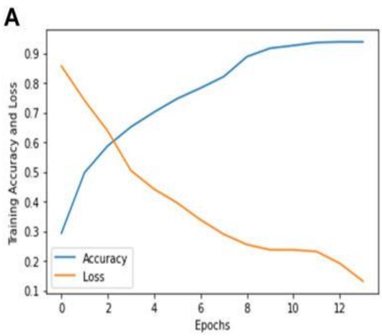

Fig4: Proposed method

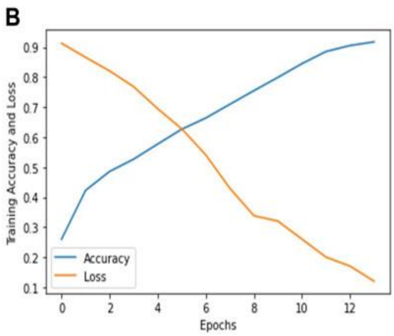

Fig5: Existing method

Our unique dataset's graphical depiction of accuracy and loss is shown above: Using ResNet-50 yields a loss and accuracy curve seen in Figure4, whereas Inception V3 yields a loss and accuracy pattern depicted in Figure5.

Table:1 Evaluation of existing and proposed model performance

Existing Models	Accuracy
Support Vector Machine (SVM)	92%
KNN	74%
Inception V3	85%
Proposed Models	**Accuracy**
CNN, GoogLeNetVGG-16, ResNet-50	95%

Table-1 shows the Comparisons are made between the performance of currently used and proposed models for picture categorization. The suggested models, which include CNN, VGG-16, and ResNet-50, display significantly greater accuracies than the base-line methods, which are SVM, KNN and Inception V3 with 92%, 74%, and 85%, respectively. That the presented models perform better and have more potential to enhance picture categorization jobs.

7 CONCLUSION

A deep learning-based architecture is suggested for medical picture categorization, in which the images themselves are used as training data. An accurate diagnosis is essential in the modern day since it allows for targeted investigation of medical diseases. Doctors and other medical professionals may be able to get more done with the support of accurate computer-based picture analysis. We created a system that uses a deep convolutional neural network to aid doctors in making accurate diagnosis. The suggested approach has been shown to perform effectively in experiments conducted on a variety of existing datasets. This paper analyzed many medical picture datasets for classification and detection issues.

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