



Aarogya Bharat

¹Aman Dubey, ²Anubhav Kumar, ³Anuj Trivedi, ⁴Bhavesh Modi, ⁵Pir Mohammad

^{1,2,3,4,5}Acropolis Institute of Technology and Research Indore

ABSTRACT—

In recent years, some researchers have used various machine learning-based approaches to develop autonomous disease detection systems, and early disease identification may help to reduce the number of people who die. The disease detection models aim to bring the medical and artificial intelligence (AI) fields together so that people can understand how well AI and medicine can work together. To better understand the role of Artificial intelligence in the medical field, we plan to conduct a comprehensive study on AI applications for the healthcare sector. First, we'll go over the highlights and motives for using AI in the healthcare industry. Following that, we go over machine-learning-based algorithms for integrating AI and the healthcare sector in depth. Next, we go over the technical problems of AI in the medical industry first, and then show how machine learning can help. We also look into the impact of machine learning in the medical field. Moreover, we also present several notable initiatives that demonstrate the importance of machine learning in healthcare applications and services. Finally, discuss some existing issues in disease identification and suggest future research and development areas that will lead to the usage of machine learning in the healthcare sector.

Keywords—pandemic,keras,datasets,X-rays (key words)

Introduction

Rapid advances in technology and the healthcare industry have contributed to changes in people's lifestyles and socioeconomic situations in recent years, raising the risk of people contracting numerous diseases. Major diseases such as brain tumors, lung cancer, and pneumonia, among others, have a global impact. In 2019, roughly 86000 individuals were diagnosed with a brain tumor, according to the World Health Organization, with a 35 percent average survival rate, and breast cancer is a terrible disease that kills one in every five people worldwide, or 1.59 million people, accounting for 19.4 percent of all deaths. With over 37 million verified cases and more than 1 million deaths globally, the coronavirus pandemic has impacted various countries, and has brought diseases like pneumonia to the forefront. These major disorders increase societal pressure and healthcare costs, thereby impacting the patient's overall health. The primary goal of disease detection is to determine whether or not a person is at risk of contracting one or more serious diseases. This necessitates the consideration of numerous issues, which takes a significant amount of manpower and financial resources.

Deep learning uses algorithms to identify and analyze patterns in medical images. In a variety of medical applications, deep learning has improved to the point where it is currently the top of the line. Deep learning can process large amounts of data and extract multiple data features. Deep learning is utilized in domains such as image recognition, natural language processing, and speech recognition. Deep learning has grown into a profound level, also referred to as a deep neural network (DNN), as more people seek models, more data, and more processing capacity.

Problem Formulation

By extracting characteristics and classifying them, the deep learning model achieves great results. However, the current system's model interpretability is inadequate. It is necessary to connect medical domains and deep learning interpretability of models. The interpretability of models refers to the degree to which humans can comprehend decision-making logic. Deep learning's problem is that it is entirely data-driven, with no regard for prior domain expertise or experience, as well as risk considerations. The deep learning model has been fully trained, and new data is being fed into it, with detection results being generated. The model, on the other hand, only presents the classification results depending on the input data and does not indicate how to detect or predict. The model's credibility is determined by its interpretability. As a result, future research should pay more attention to model interpretability.

The most difficult aspect of model training is still data quality. High-quality medical data is required for Deep learning models to perform well in prediction and diagnosis. Despite the ease with which medical data can be obtained under current circumstances, the data quality is still poor. To offer a proprietary label to many medical facts, medical experts must have a great deal of experience. Image feature analysis is particularly significant, because medical data sets are kept in different institutions due to several privacy issues. A large majority of the data sets cannot be used in legitimate research since they are closed rather than open. Many novel models are hindered by the inability to obtain proper training.

Literature Review

Breast cancer is one of the most common causes of cancer worldwide. Robust and Automated systems have been developed to lessen this burden and to help the patients to conduct the early assessment of the skin lesion. Mostly this system available in the literature only provides skin cancer classification. Treatments for it are more effective and less disfiguring when found early and it is challenging research due to similar characteristics of skin diseases. In this project we attempt to detect skin diseases. A novel system is presented in this research work for the diagnosis of the most common skin lesions (Melanocytic nevi, Melanoma, Benign keratosis-like lesions, Basal cell carcinoma, Actinic keratoses, Vascular lesion, Dermatofibroma). The proposed approach is based on the pre-processing, Deep learning algorithm, training the model, validation and classification phase. Experiments were performed on 10010 images and 93% accuracy is achieved for seven-class classification using Convolutional Neural Networks (CNN) with the Keras Application API.

Methodology

Image Acquisition Phase:

The acquisition of disease-related images is the initial phase of the disease detection model. Because the CNN technique is used, the model must be trained on a vast number of images. In the scope of this research, images provide critical data for the diagnosis of different diseases. Images such as CT scans and chest X-rays can be used. The first phase's output comprises images, which are fed into the model for training. Here image dataset is acquired from Kaggle.

Data Pre-processing Phase

The image is modified at this stage to increase image quality. Because the images in the dataset are of varying sizes, they are adjusted to have a shape of $(224, 224) = (\text{image width}, \text{image height})$ so as to feed it as an input to the neural network, as all images must have the same shape. To expand the quantity of data available, data augmentation is performed on the images. To scale pixel values to the range 0–1, normalization is used. Feature extraction is done so that the DNN model can find relevant features that can be used to classify certain classes. The result is a series of images that have been upgraded in quality or have undesired elements removed.

Training Phase

The selection of a deep learning algorithm is done in the third phase, training. The previously described CNN is an example of a deep learning algorithm. Algorithms can learn in a variety of ways. Certain algorithms work best with specific types of data. CNN is adept at using images. The type of data should determine which deep learning method is used. The models created from the data learned are the result of this step.

Classification Phase

The last phase is classification, in which the trained model predicts which class an image belongs to. For example, if a model has been trained to distinguish between normal and tumorous brain in MRI images, it should categorize images accordingly. The model assigns a probability score to each image, indicating how probable it is that the image belongs to a given class.

Data Augmentation is a technique for increasing training datasets without having to gather new images. Data augmentation alters the original images in some way. This is accomplished by using various processing techniques including rotations, flips, zooming, and adding noise, among others. Large training datasets are significant in deep learning since they improve the training model's accuracy. It also aids in the avoidance of overfitting. The downsides of data augmentation include increased training time, transformation computation costs, and higher memory expenses.

Machine Learning

The technology we apply in the project is Machine Learning. Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed.

Colaboratory

Colaboratory, or "Colab" for short, is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis and education. More technically, Colab is a hosted Jupyter notebook service that requires no setup to use, while providing free access to computing resources including GPUs.

Jupyter Notebook

The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and explanatory text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, machine learning and much more.

JavaScript

JavaScript, often abbreviated as JS, is a programming language. JavaScript is high-level, often just-in-time compiled, and multi-paradigm. It has curly-bracket syntax, dynamic typing, prototype-based object-orientation, and first-class functions. Alongside HTML and CSS, JavaScript is one of the core technologies of the World Wide Web. JavaScript enables interactive web pages and is an essential part of web applications. The vast majority of websites use it for client-side page behavior, and all major web browsers have a dedicated JavaScript engine to execute it.

Feature extraction:

The accuracy of image classification depends mainly on image feature extraction. More discriminated features better will be the classification result. In this study we extracted three levels of information, pixel level the pixel information as feature itself, shape and texture information at global and local level. Color information is not included as we are dealing with gray scale images.

Convolutional Neural Network (CNN)

A convolutional neural network (CNN or ConvNet), is a network architecture for deep learning which learns directly from data, eliminating the need for manual feature extraction. CNNs are particularly useful for finding patterns in images to recognize objects, faces, and scenes. The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision. For example, given many pictures of cats and dogs it learns distinctive features for each class by itself.

A. Figures

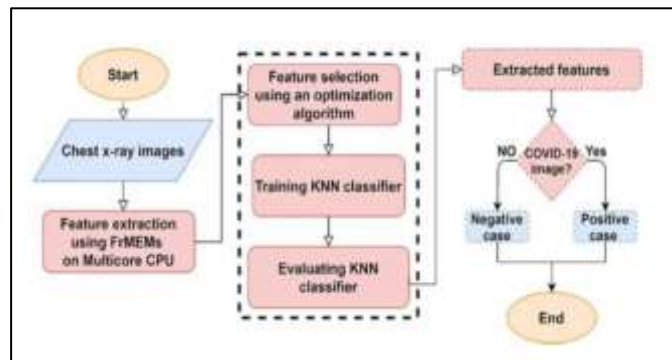


Fig.1 Flowchart

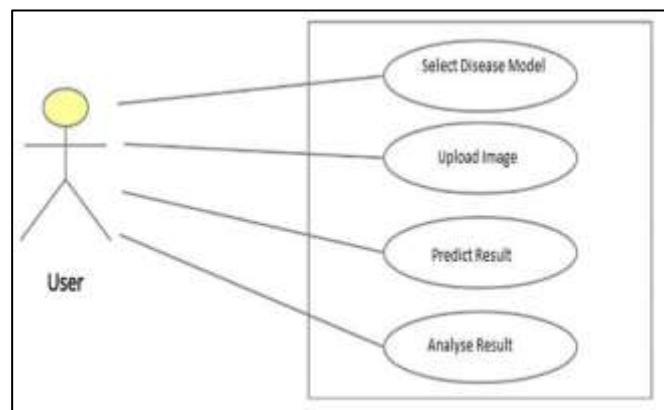


Fig.2 Unified Modeling Language



Fig. 3 Home Page

Conclusion

Under the backdrop of artificial intelligence and deep learning techniques, the future of medical healthcare has more modern prospects. Deep learning has emerged as a primary driving force for future progress in the face of medical data instability, thanks to its unique feature processing approach and variable model structure. The deep learning models are linked together and learn from one another, creating a more complex deep learning system network which contributes to the improvement of the medical profession by assisting in the development of medical diagnosis and practical applications. We have highlighted the most common deep learning approaches in this study. The approach and existing challenges, as well as the limitations of deep learning are also highlighted. We also go over the many security and privacy issues and obstacles that have been encountered. We also highlight several relevant papers, as well as various research concerns that need to be addressed further.

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