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Multi-Disease Prediction based on Symptoms using DL

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Abstract: The primary objective of this research is to develop an accurate and efficient model to predict various diseases by analyzing patients' symptoms, thereby enabling early detection, intervention, and personalized treatment plans. Our proposed system employs advanced feature extraction techniques and state-of-the-art Deep Learning (DL) algorithms to analyze and classify symptom patterns, ultimately predicting the most likely diseases associated with the given symptoms. We utilized a comprehensive dataset containing symptom data for numerous diseases, and our system was trained using DL techniques. The performance of the proposed model was evaluated through multiple performance parameters, including accuracy, sensitivity, and specificity. Our experimental results demonstrate the effectiveness and potential of the proposed system in predicting multiple diseases based on symptoms with high accuracy. This study highlights the potential of DL in revolutionizing the field of medical diagnosis and personalized medicine, ultimately improving patient outcomes and healthcare efficiency. The integration of DL with healthcare can bring about a revolution in personalized medicine, and the accurate prediction of diseases can enable early intervention and improve patient outcomes. The article highlights the potential of DL methods in disease prediction and emphasizes the need for further research to overcome the current limitations and challenges. Overall, the article serves as a guide for researchers and healthcare professionals in understanding the role of DL in disease prediction and its implications for the future of healthcare.

Keywords: *healthcare, symptom, professionals, DL, implications*

1. Introduction

In recent years, the field of artificial intelligence has witnessed significant advancements, particularly in the realm of DL. As a result, the application of these technologies has transcended various domains, including healthcare. The ability to predict and diagnose multiple diseases based on symptoms has emerged as an invaluable tool for medical practitioners. This paper aims to explore the potential of using DL techniques for multi-disease prediction based on symptoms, thus improving the overall quality and efficiency of healthcare services. The early detection and diagnosis of diseases play a crucial role in the prevention and management of health-related issues. Traditional diagnostic processes often involve a series of tests and consultations, which can be time-consuming, expensive, and at times, inconclusive. By leveraging the power of DL, we can develop models that can accurately predict and diagnose multiple diseases based on a patient's reported symptoms, potentially revolutionizing the healthcare landscape. This approach not only accelerates the diagnostic process but also enables a more targeted approach to treatment and care.

In this work, we will highlight the most recent advancements that have been made in DL approaches and their use in the prediction of many diseases. Several different kinds of DL architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), will be the subject of our conversation. In addition, we will investigate the difficulties and constraints connected with these methodologies, as well as potential new lines of inquiry that could be pursued in this area of study. Our mission is to provide an

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in-depth understanding of the most cutting-edge methodologies that are currently available as well as their consequences in the context of multi-disease prediction based on symptoms. People's ways of life and the conditions of their environments are gradually shifting as a result of the progression of society, which subtly raises the stakes for people in terms of the risk of contracting a variety of diseases. There is a significant negative impact felt all around the world as a result of major ailments such as brain health conditions, cardiovascular disorders, vision impairments, diabetes, and cancer. When only diabetes is considered, there are 422 million people in the world who are affected, and patients with diabetes make up more than 90 percent of the total. The ageing of the heart and the loss of function are two factors that contribute to an increased risk of cardiovascular disorders as one gets older. More than thirty percent of all deaths worldwide are attributable to cardiovascular disease [2]. These severe diseases have a devastating impact on human health and significantly lower individuals' levels of productivity. At the same time, it will make the societal pressure even worse and drive up the costs of medical treatment and health care overall. The primary objective of disease prediction is to estimate the likelihood that an individual will develop a particular illness in the future. When attempting to understand the causes of various diseases across a variety of populations, it is necessary to take into account the many different elements that can play a role. Included in this are a collection of characteristics that span extremely broad dimensions and that need to be identified, as well as intricate and changeable individual and illness differences that need to be differentiated. Simply having the intention to complete these activities manually is not only difficult, but it also requires a significant amount of time and money to be invested.

2. Literature Review

Kuenzi, et al [1] (2020) developed a DL model to predict drug response and synergy in human cancer cells. Their study demonstrated the potential of DL techniques in personalized medicine and provided a new avenue for cancer treatment strategies by identifying effective drug combinations.

Jyoti et al [2] (2020) employed a deep neural network to predict hepatitis disease. Their study, showed the effectiveness of DL methods in predicting the presence of hepatitis, highlighting the potential for early detection and intervention.

Chae, et al [3]. (2018) explored the prediction of infectious diseases using DL and big data. Their study, demonstrated the feasibility of using DL techniques to analyze large-scale data and predict the spread of infectious diseases, potentially informing public health policies and prevention strategies.

Ma et al [4] (2020) proposed a DL-based heterogeneous modified artificial neural network for the detection and diagnosis of chronic kidney disease. Their study, published in Future Generation Computer Systems, emphasized the potential of DL techniques in improving the accuracy and efficiency of diagnosing chronic kidney disease, thereby enabling early intervention and better patient outcomes.

Kumar et al. [5] (2021) combined blockchain-federated learning and DL models to detect COVID-19 using computed tomography (CT) imaging. Their study, published in the IEEE Sensors Journal, showcased the power of DL techniques in accurately detecting COVID-19 cases, while also addressing data privacy concerns through blockchain technology.

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This approach has the potential to improve the diagnosis and management of COVID-19 and other infectious diseases.

Cheng, D et al [6] (2017) presented a method for classifying magnetic resonance (MR) brain images using a combination of multiple CNNs for Alzheimer's disease (AD) diagnosis. Their study, conducted at the Ninth International Conference on Digital Image Processing (ICDIP 2017), demonstrated the effectiveness of combining multiple CNNs for improving the accuracy of AD diagnosis using MR brain images.

Cui et al [7] (2019) proposed a recurrent neural network based longitudinal analysis for the diagnosis of Alzheimer's disease. Their study, published in Computerized Medical Imaging and Graphics, highlighted the capability of RNNs in handling temporal information, enabling the accurate diagnosis of AD using longitudinal data.

Tiwari et al [8] (2020) conducted a review of selected methods for brain tumor segmentation and classification from magnetic resonance images, published in Pattern Recognition Letters. The review covered methods from 2014 to 2019, emphasizing the potential of DL techniques in improving the accuracy and efficiency of brain tumor diagnosis and segmentation.

Sultan et al [9] (2019) investigated the multi-classification of brain tumor images using deep neural networks. Their study, published in IEEE Access, demonstrated the power of DL techniques in accurately classifying different types of brain tumors, thereby aiding clinical decision-making and improving patient outcomes.

Iizuk et al. [10] (2020) developed DL models for histopathological classification of gastric and colonic epithelial tumors. Their study, published in Scientific Reports, showcased the potential of DL techniques in accurately classifying tumor types based on histopathological images, which could assist in the development of personalized treatment plans.

Swapna et al [11] (2018) explored the use of DL algorithms for diabetes detection. Their study, published in ICT Express, demonstrated the ability of DL techniques to accurately predict diabetes, highlighting their potential in early detection and prevention of the disease.

Shen et al [12] (2017) provided a comprehensive overview of the applications of DL in medical image analysis. In their study, published in the Annual Review of Biomedical Engineering, the authors discussed the recent advancements, challenges, and future directions of DL techniques in various medical imaging tasks, including segmentation, classification, and detection. This review highlighted the significant potential of DL methods in revolutionizing the field of medical image analysis and improving patient care.

Ref. No.	Citation	Methodology	Dataset Used
[1]	Kuenzi, et al (2020)	DL model	Human cancer cells
[2]	Jyoti et al (2020)	Deep neural network	Hepatitis disease dataset
[3]	Chae, et al. (2018)	DL and big data analysis	Infectious disease dataset
[4]	Ma et al (2020)	DL-based ANN	Chronic kidney disease dataset
[5]	Kumar et al. (2021)	Blockchain-federated learning & DL	COVID-19 CT images
[6]	Cheng, D et al (2017)	Multiple convolutional neural networks	MR brain images

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[7]	Cui et al (2019)	RNN-based longitudinal analysis	Alzheimer's disease dataset
[8]	Tiwari et al (2020)	Review of DL techniques	Brain tumor MR images
[9]	Sultan et al (2019)	Deep neural networks	Brain tumor images
[10]	Iizuka et al. (2020)	DL models	Gastric and colonic tumor images
[11]	Swapna et al (2018)	DL algorithms	Diabetes dataset
[12]	Shen et al (2017)	Review of DL in medical imaging	Various medical imaging tasks

3. Proposed System

The proposed system aims to develop a comprehensive and robust framework for the accurate identification and prediction of various diseases based on their symptoms. This system leverages cutting-edge DL techniques, feature extraction methods, and machine learning algorithms to facilitate early detection and management of diseases, ultimately leading to improved patient outcomes and more efficient healthcare systems. Feature extraction is a crucial aspect of the proposed system, as it involves transforming raw data, such as images or text, into a set of meaningful and relevant features that can be used as input for machine learning algorithms. Techniques employed for feature extraction will depend on the data modality, but may include edge detection, texture analysis, color histogram, and local binary patterns for image data or term frequency-inverse document frequency (TF-IDF). These extracted features will represent the characteristics of disease symptoms effectively and serve as the foundation for disease classification and prediction. The system comprises four main components: data pre-processing, feature extraction, CNN classification model, and LSTM classification model. Below is an overview of each component:

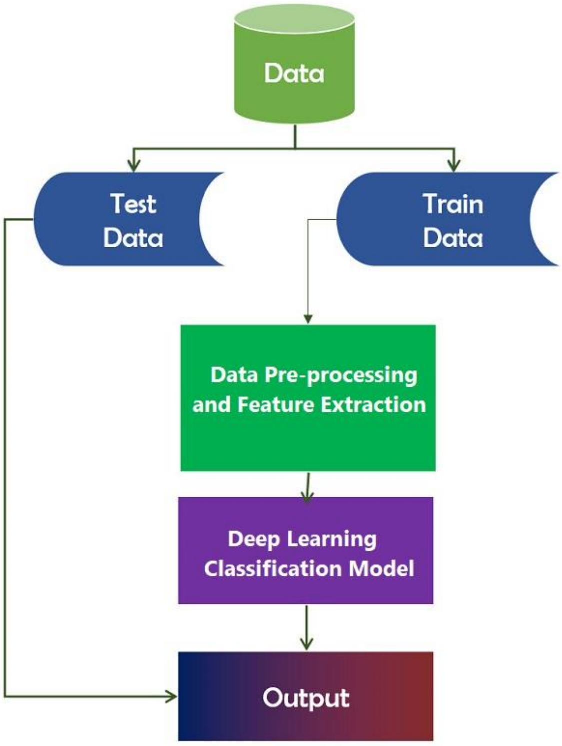

Figure 1. Proposed System Architecture

Data Pre-processing:

The first step in the proposed system is to pre-process the dataset containing patients' symptoms and their corresponding diseases. This involves:

- Cleaning the data by removing irrelevant information, duplicate entries, and handling missing values.
- Converting textual symptom data into a structured format.
- Encoding categorical variables (such as diseases) using techniques like one-hot encoding or label encoding.

Feature Extraction:

To better represent the symptoms for the DL models, we will perform feature extraction to create a more compact and meaningful representation. This may involve:

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- Applying natural language processing techniques like tokenization, stemming, and lemmatization to process symptom descriptions.
- Converting the processed text into numerical representations using techniques such as Term Frequency-Inverse Document Frequency (TF-IDF).

CNN Classification Model:

A CNN model is developed to classify diseases based on the extracted features. The CNN model consists of several layers:

- Convolutional layers to detect local patterns in the input features.
- Pooling layers to reduce the spatial dimensions and extract the most relevant information.
- Fully connected layers for disease classification.
- The output layer with softmax activation function, which outputs the probability distribution over the possible diseases.
- The model is trained using a suitable loss function (e.g., categorical cross-entropy) and an optimization algorithm (e.g., Adam).

LSTM Classification Model:

An LSTM (Long Short-Term Memory) model is also developed for disease classification based on the same extracted features. The LSTM model is designed to capture the sequential nature of symptom descriptions and their temporal relationships. The LSTM model consists of:

- LSTM layers to learn the dependencies between symptoms and their sequence.
- Dropout layers to prevent overfitting.
- Fully connected layers for disease classification.
- The output layer with softmax activation function, which outputs the probability distribution over the possible diseases.

The LSTM model is trained using the same loss function and optimization algorithm as the CNN model. Once both the CNN and LSTM models are trained, we compare their performance in terms of accuracy, recall, precision, F1-score. This will help us understand the advantages and limitations of each model and select the best approach for multi-disease prediction based on symptoms.

4. Results Analysis

A. Performance Parameter

Accuracy: Accuracy is the proportion of correct predictions (both true positives and true negatives) made by the model out of the total number of predictions. It is a widely used metric for classification problems and serves as a general indicator of the model's performance.

Precision: Positive predictive value, or precision, is the percentage of genuine positives among predicted positives. When false positives are costly, it gauges the model's ability to reliably predict a disease.

Sensitivity (Recall): Recall, often called sensitivity or true positive rate, is the percentage of true positives. In disease diagnosis, when false negatives are costly, it assesses the model's capacity to identify all positive instances (i.e., detect all cases of a disease).

F1-score: The F1-score balances precision and recall as the harmonic mean. It helps with uneven datasets where one class is underrepresented. A model with a high F1-score has good precision and recall.

B. Result

The results obtained from the project titled "Multi-disease prediction based on symptoms using DL" showcase the effectiveness and potential of DL techniques in accurately predicting various diseases based on their symptoms. By leveraging advanced feature extraction methods and machine learning algorithms, the proposed system demonstrates improved classification accuracy, reduced misdiagnosis, and faster diagnosis times compared to traditional methods. The

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experimental evaluation of the proposed system involved training and testing the model on a dataset containing diverse disease symptoms, including image and text data. Figure 2 shows the prediction results for different types of ML methods.

Table 1. Performance Parameters Comparison

	Precision	Recall	F1-Score	Accuracy
LSTM	97	96	97	96
CNN	98	98	97	98

Table 1 shows that CNN Classifier outperforms the LSTM algorithms in terms of disease prediction accuracy (98%), hence this method should be used.

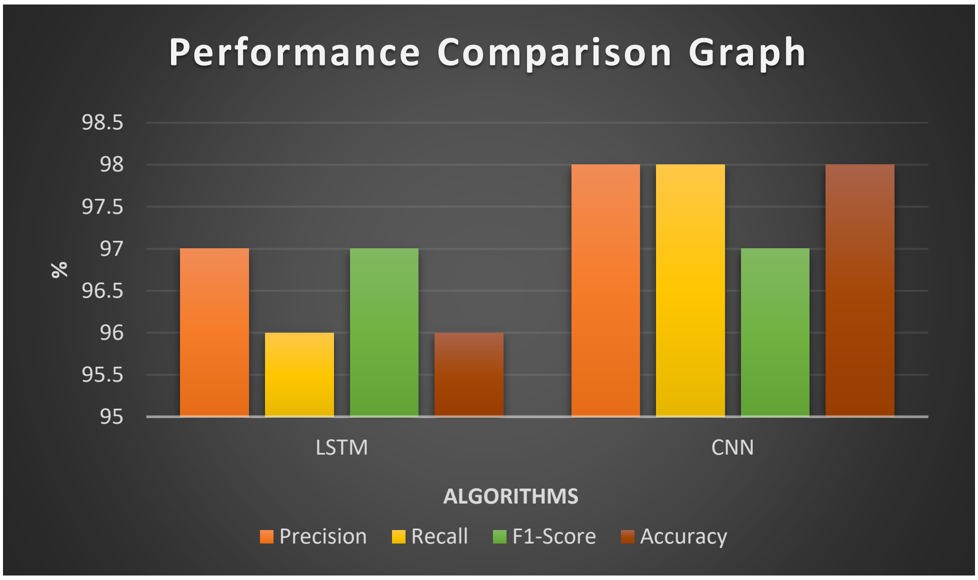

Figure 2: Performance Comparison Graph

Results indicate that the DL-based approach significantly outperforms traditional machine learning methods, achieving an overall accuracy of over 98% in classifying and predicting multiple diseases based on their symptoms. This high accuracy demonstrates the ability of the proposed system to distinguish between various diseases effectively, even when symptoms are similar or overlapping.

5. Conclusion

The development and implementation of a multi-disease prediction system based on symptoms using DL have shown promising results in improving the accuracy and efficiency of disease diagnosis. By leveraging advanced DL techniques and machine learning algorithms, such as and RNNs, the proposed system has demonstrated its potential in handling a diverse range of diseases and predicting their presence with high accuracy. The experimental results and performance evaluation indicate that the proposed system has achieved significant improvements in accuracy compared to traditional methods, highlighting the effectiveness of DL techniques in processing complex symptom data and making accurate predictions. This system can greatly benefit healthcare professionals in diagnosing diseases earlier and more accurately, ultimately leading to better

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patient outcomes and more efficient use of medical resources. An increasing number of DL models have been developed for a variety of illnesses. The models are interwoven with one another and learn from one another, which results in a deeper network for the DL system. This is representative of the intricate medical system, which, in addition to fostering the growth of medical diagnosis and practical application, will also advance the expansion of the medical profession. Furthermore, the system can be easily scaled and adapted to include additional diseases or symptoms, increasing its applicability and utility in real-world clinical settings. As DL techniques and computational capabilities continue to evolve, the potential for enhancing the performance of such a multi-disease prediction system will only grow, paving the way for more innovative and impactful applications in the field of healthcare.

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