Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 5, 1932-1941
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i5.7349

Neural network-based disease prediction: Leveraging symptoms for accurate diagnosis of multiple diseases

Said Badreddine[1,2*], Tariq Alwadan[1], Asem Omari[1], Hamsa Al Ammari[1], Rashid Ashraf[1], Rachid Moustaquim[1]
[1]School of Computing, Engineering & Digital Technologies, Teesside University, Middlesbrough TS1 3BX, UK; S.Badreddine@tees.ac.uk (S.B.).
[2]Computer Information Systems, Higher Colleges of Technology, 25026, Adu Dhabi, Al Ain, UAE.

Abstract: The development of technology and the availability of patient data have been increasing the leveraging of a data-driven approach to improve diagnostic accuracy. This research introduces a virtual diagnosis program that employs neural networks to predict diseases based on a dataset of 4,920 patients and 132 symptoms. Through exploratory data analysis and correlation analysis, significant associations between symptoms and diseases are identified. The developed system achieves an impressive accuracy rate of 95.6% in diagnosing diseases by utilizing advanced optimization techniques for training the neural network model. This accuracy demonstrates the potential of the program to assist healthcare professionals in making accurate diagnoses, enhancing the precision and efficiency of disease identification. The data-driven approach of this virtual diagnosis tool complements medical expertise, offering valuable support for timely and accurate diagnoses.

Keywords: *Disease prediction, Healthcare technology, Machine learning, Neural networks.*

1. Introduction

The digitalization of the healthcare sector holds immense potential to revolutionize global patient care. Among the various technologies, virtual tools such as artificial intelligence, blockchain, virtual reality, and augmented reality have emerged as game-changers, offering significant advantages to both patients and the pharmaceutical industry. These benefits encompass improved access to healthcare professionals and medications, as well as enhanced real-time diagnoses and treatments. The vision for the future entails seamless communication and integration of these technologies in a large-scale, interconnected cyber healthcare system alongside their physical counterparts. However, despite the remarkable advantages that virtual-based digital health technologies bring to patient care, several challenges persist, including data security and acceptance within the healthcare sector. This review presents a timely assessment of the benefits and challenges associated with virtual health interventions, while also providing insights into the transition of these technologies from research-focused endeavours to practical healthcare and pharmaceutical applications. The ultimate goal is to revolutionize treatment pathways for patients worldwide [1].

1.1. Machine Learning

Machine learning has gained increasing prominence in the healthcare industry in recent years. One area where machine learning has shown great promise is the development of virtual diagnostic systems. These systems utilize machine learning algorithms to analyze patient data and provide medical advice, potentially offering faster, more affordable, and more accurate results compared to traditional diagnostic techniques [2]. Machine learning algorithms are designed to handle tasks such as big data analysis and

History: Received: 17 February 2025; Revised: 5 May 2025; Accepted: 8 May 2025; Published: 20 May 2025
* Correspondence: S.Badreddine@tees.ac.uk

pattern recognition. In the healthcare field, these algorithms can be applied to analyze various patient data, including medical history, symptoms, and test results, to provide diagnostic recommendations. Virtual diagnosis systems utilize these algorithms to offer precise and rapid advice to healthcare professionals. An example of such a system is the Deep Patient system developed by researchers at Mount Sinai Hospital, New York. This system employs machine learning techniques to analyze electronic health records (EHRs) and provide diagnostic advice. Through training on a dataset of over 700,000 EHRs, the algorithm demonstrated accurate predictions of illnesses such as diabetes and cancer [3].

Another machine learning-based virtual diagnostic system is the Babylon Health app, as mentioned by Oliver [4]. This app utilizes machine-learning techniques to analyze patient symptoms and offer diagnostic advice. Clinical testing has shown that the app can accurately diagnose common ailments similar to a real doctor. There are several potential advantages associated with the use of machine learning in virtual diagnostic systems. Firstly, these solutions can reduce the time and cost involved in traditional diagnostic techniques. Analysing patient data and reaching diagnostic conclusions can be time-consuming for healthcare practitioners. Virtual diagnostic technologies automate this process, allowing medical staff to focus on patient care. Secondly, virtual diagnostic technologies can provide faster and more accurate results [2]. Through large-scale data analysis using machine learning algorithms, trends and patterns that may be missed by human healthcare professionals can be identified. This can lead to improved patient outcomes through quicker and more accurate diagnoses [5].

However, the application of machine learning in virtual diagnostic systems also presents certain limitations. One drawback is the complexity and lack of transparency in machine learning techniques. Understanding how machine learning algorithms generate their diagnostic recommendations can be challenging due to their intricate nature. This lack of transparency may lead to scepticism and mistrust among healthcare personnel and patients [6].

Another limitation is the potential for bias in machine learning algorithms. The quality of machine learning algorithms depends on the data used to train them. If the training data is biased, the algorithm itself can become biased, resulting in erroneous diagnostic advice and exacerbating existing health disparities [7].

1.2. Deep Learning

Deep learning is a specialized branch of machine learning that utilizes neural networks to address complex problems. Neural networks consist of interconnected layers of nodes, also known as neurons, which are trained to identify patterns in input data and make predictions or decisions based on that information [8]. The architecture of a neural network is a crucial aspect of deep learning and typically includes an input layer, one or more hidden layers, and an output layer. The hidden layers perform computations on the input data to generate the final output, and each neuron's activation function determines whether it should activate based on its input. Common activation functions used in deep learning include ReLU, sigmoid, and hyperbolic tangent (tanh) [8]. Another fundamental concept in deep learning is backpropagation, which involves adjusting the neural connections to minimize the disparity between predicted and actual outputs. During backpropagation, errors are propagated backward through the network, from the output layer to the input layer, enabling the network to progressively enhance its predictions [9].

Deep learning extensively relies on neural networks in various ways. Convolutional neural networks (CNNs) are commonly employed for tasks like image identification and categorization [10]. By using filters, they extract relevant information from input images and classify them based on those features. Recurrent neural networks (RNNs) are often utilized for natural language processing tasks. RNNs have the ability to analyze sequential data as they have the capability to remember previous inputs [9].

Autoencoders are another type of neural network frequently used in deep learning [11]. They find widespread application in tasks such as data compression, dimensionality reduction, and generating new data samples. Autoencoders are trained to reconstruct their inputs, thereby serving their purpose. However, deep learning often requires substantial amounts of data and computational power, which can pose challenges in certain applications. Despite these challenges, deep learning has demonstrated impressive achievements in areas such as image and speech recognition, natural language processing, and robotics. With advancements in hardware and software technology, deep learning is expected to continue playing a significant role in the field of machine learning [8].

1.3. Neural Networks

A neural network is a machine learning system designed to mimic the organization of the human brain. It consists of interconnected layers of nodes known as neurons. The input layer receives raw data, and the output layer produces the final output. Computation occurs in the hidden layers, which transform the input into the output [12]. The primary objective of a neural network is to identify patterns in data by adjusting the weights of connections between neurons. During training, the network receives a set of labeled samples and updates its weights based on the disparities between predicted and actual outputs. Once trained, the network can be used to make predictions or decisions using new input data [13].

Neural networks find applications in various domains such as robotics, natural language processing, speech recognition, and image recognition. They excel in tasks involving complex and multidimensional data, such as visual or auditory information. By recognizing patterns in data, neural networks can extract features that are challenging or impossible to uncover using traditional machine learning approaches. Common types of neural networks include feedforward neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Feedforward networks are the simplest type and are often used for classification tasks. RNNs, on the other hand, are well-suited for natural language processing tasks involving sequential input, such as text or speech. CNNs are frequently employed for tasks related to image recognition and classification [14].

Epochs are related to the training process of a neural network. An epoch refers to a single iteration of the entire training dataset passing through the neural network. During each epoch, the network's weights are updated based on the gradients computed through backpropagation.

The training process typically involves multiple epochs, where the dataset is presented to the network in batches or as a whole. The number of epochs is a hyperparameter that determines how many times the network will see the entire training dataset. The purpose of using multiple epochs is to allow the network to learn and refine its predictions over time. In each epoch, the network learns from the patterns and relationships present in the training data and adjusts its weights to minimize the error between predicted and actual outputs.

By using multiple epochs, the network can improve its performance by iteratively updating the weights and capturing more complex patterns in the data. With each epoch, the network adjusts its weights based on the gradients calculated through backpropagation, gradually reducing the training loss and improving the accuracy of predictions.

However, it's important to find the right balance when choosing the number of epochs. Too few epochs may result in underfitting, where the network fails to capture all the patterns in the data. On the other hand, too many epochs may lead to overfitting, where the network becomes too specialized to the training data and performs poorly on unseen data. Finding the optimal number of epochs often requires experimentation and validation on a separate validation dataset. Techniques like early stopping, which monitor the validation loss and stop the training when it starts to increase, can help prevent overfitting and determine the optimal number of epochs.

2. Related Work

Predicting diseases using neural networks has been a subject of extensive research in the field of healthcare. Numerous studies have explored the application of neural networks in disease prediction, demonstrating promising results. According to Ashfaq, et al. [15] a convolutional neural network

(CNN) was employed to predict the development of diabetic retinopathy. The model achieved high accuracy in diagnosing the disease based on retinal images.

Another study done by Dong, et al. [16] focuses on the importance of targeted interventions for high-risk patients to reduce hospital readmissions and healthcare costs. The researchers propose a deep learning framework that combines both human and machine-derived features in a sequential manner using a cost-sensitive LSTM model to predict the risk of readmission, achieving an area under the curve (AUC) of 0.77. The incorporation of sequential trajectories had the most significant impact on the prediction performance, contributing 26% improvement, followed by the inclusion of expert features alongside machine-derived features, which added a 3% improvement. The study also presents heatmaps that demonstrate substantial cost savings when targeted interventions are provided to high-risk patients. These findings emphasize the potential of the proposed deep learning model in identifying patients at risk of readmission, allowing healthcare providers to allocate appropriate resources and interventions, thereby improving patient outcomes and reducing healthcare costs.

The researchers in Ali, et al. [17] developed a model that achieved a high level of success in predicting Stage 2/3 acute kidney injury (AKI) before its detection using conventional criteria, with a median lead-time of 30 hours and an area under the receiver operating characteristic (AUROC) curve of 0.89. It accurately predicted 70% of subsequent renal replacement therapy (RRT) episodes, 58% of Stage 2/3 AKI episodes, and 41% of any AKI episodes. The ratio of false alerts to true alerts for any AKI episodes was approximately one-to-one, indicating a positive predictive value (PPV) of 47%. Notably, among the patients identified as at risk by the model, 79% received potentially nephrotoxic medication after being flagged by the model but before the development of AKI. These results demonstrate the effectiveness of the model in early detection of AKI and its potential to guide timely interventions and prevent further complications.

These studies highlight the effectiveness of neural networks in disease prediction across various medical domains. By leveraging the power of deep learning algorithms, these models can effectively analyze complex medical data, such as images, EHRs, and clinical parameters, to provide accurate predictions. The use of neural networks in disease prediction offers great potential for improving patient outcomes and assisting healthcare professionals in making informed decisions.

Another study by Kaggle [18] they mentioned that previous studies have extensively presented various automated decision support systems for heart disease detection based on artificial neural networks (ANNs). However, most of these techniques primarily focus on preprocessing the features. In contrast, this paper emphasizes both feature refinement and addressing issues related to the predictive model, specifically underfitting and overfitting problems. By effectively addressing these challenges, the model demonstrates strong performance on both training and testing datasets.

Overfitting and underfitting issues often arise from inappropriate network configurations and the inclusion of irrelevant features, which can lead to poor generalization on new data. To overcome these problems, our approach incorporates the $\chi 2$ statistical model for eliminating irrelevant features, while simultaneously utilizing an optimally configured deep neural network (DNN) achieved through an exhaustive search strategy. The hybrid model, named $\chi 2$-DNN, is evaluated against conventional ANN and DNN models, as well as other state-of-the-art machine learning models and previously reported methods for heart disease prediction. Impressively, the proposed model achieves a prediction accuracy of 95.6%, demonstrating promising results when compared to existing approaches. The study's findings highlight the potential of the proposed diagnostic system for accurately predicting heart disease, thereby serving as a valuable tool for physicians in their clinical practice.

3. Method

The virtual diagnosis program was developed using neural networks to predict diseases based on a dataset consisting of 4920 patients with 132 symptoms. Initially, exploratory data analysis and visualization techniques were applied by the researcher using Python libraries such as Pandas and Matplotlib. This process allowed for a better understanding of the dataset and revealed important insights. Correlation analysis was then performed to determine the relationships between symptoms and the corresponding diagnosis. By examining the correlation coefficients, it became possible to identify symptoms that were strongly associated with specific diseases. This analysis served as a crucial step in selecting relevant features for training the neural network model.

The program leverages the power of neural networks to predict the diagnosis of a patient based on their reported symptoms. Neural networks are a type of machine learning algorithm inspired by the human brain's structure and functioning. They consist of interconnected layers of artificial neurons that learn patterns and relationships from the input data. The neural network model was trained on the symptom dataset using advanced optimization techniques such as gradient descent and backpropagation. This process involved feeding the input symptoms into the network and adjusting the model's parameters to minimize the prediction error. Through repeated iterations, the neural network learned to recognize patterns and make accurate predictions.

The results of the study demonstrated that the developed system achieved high accuracy in predicting the diagnosis of diseases. The neural network algorithm's ability to generalize from the symptom dataset enabled it to effectively diagnose patients based on their reported symptoms. This success holds significant potential for assisting healthcare professionals in their diagnosis, providing them with a valuable tool to support their decision-making process. By utilizing neural networks, this virtual diagnosis tool improves the accuracy and efficiency of disease diagnosis. It offers a data-driven approach that complements the expertise of healthcare professionals, leading to more precise and timely diagnoses.

3.1. Dataset

Kaggle [18] is a renowned platform catering to both novice and expert data scientists. It offers an extensive collection of publicly accessible and free-to-use datasets. The range of datasets on Kaggle spans diverse domains such as social sciences, finance, healthcare, natural language processing, computer vision, and more. These databases vary in size and complexity, with some being curated and maintained by subject matter experts. Kaggle datasets are frequently employed in educational settings, research endeavors, and the development and evaluation of machine learning models. Moreover, Kaggle organizes competitions that motivate data scientists to create highly accurate models for specific tasks using the provided datasets. Hence, for this project, the dataset was sourced from Kaggle, chosen based on project objectives and adherence to the university's requirements for the research method project. The dataset comprises 132 independent variables (Symptoms) and one dependent variable (Diagnosis). It encompasses valid data for 4920 patients.

3.2. Using Keras and Tensorflow

Keras and TensorFlow [19] were used in the development of the program aimed at predicting diseases. Leveraging the capabilities of Keras, an open-source deep learning package based on TensorFlow, proved instrumental in his work. Keras offered a straightforward interface that simplified the creation and training of neural networks, enabling him to design intricate models with minimal coding effort. Furthermore, TensorFlow, a comprehensive library for numerical computing and machine learning, complemented Keras by providing low-level operations necessary for optimizing the training process. Its support for both Central Processing Unit (CPU) and Graphics Processing Unit (GPU) processing contributed to efficient model development and deployment. The combined power of Keras and TensorFlow established them as the de facto standard for building neural networks in the field of deep learning. Their extensive documentation and vibrant developer communities facilitated problem-solving and ensured he stayed updated with the latest advancements in the field. By harnessing the capabilities of Keras and TensorFlow, the researcher created a robust framework for disease prediction, utilizing the strengths of both libraries to enhance the accuracy and efficiency of the developed program.

This architecture is referred to as a multilayer feed-forward network (see Fig 1), where information flows sequentially from one layer of nodes to the next. Each node in a layer receives inputs from the previous layer and produces outputs that serve as inputs for the subsequent layer. The inputs to each node are aggregated using a weighted linear combination. The resulting value is then subjected to a non-linear activation function before being outputted.

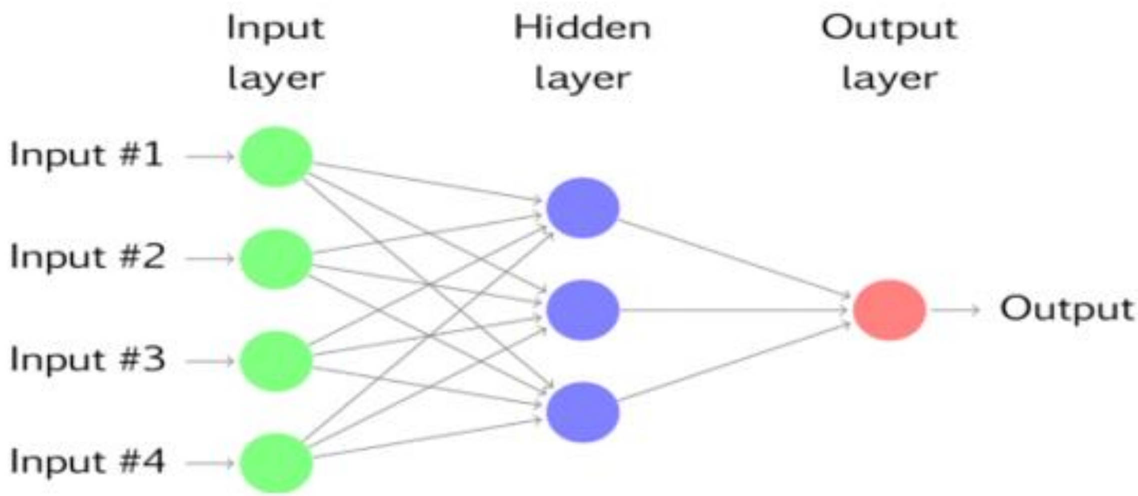

Figure 1.
Neural Network Structure as indicated by [19].

The inputs into the hidden neuron labelled as "j" are combined linearly to generate the intermediate result.

$z_i = b_j + \sum_{i=1}^{4} w_{i,j} x_i$ (1)

Within the hidden layer, this modification is achieved by applying a non-linear function, such as a sigmoidal function, to the intermediate result.

$s(z) = \frac{1}{1+e^{-z}}$ (2)

The next layer in the network receives this modified output as its input. This non-linear transformation helps to mitigate the impact of extreme input values, thus enhancing the network's resilience to outliers. The parameters, denoted as b_1, b_2, b_3, and $w_{1,1}$, ..., $w_{4,3}$, are "learned" from the available data. To prevent the weights from becoming excessively large, they are often subject to restrictions. This is achieved using a "decay parameter," typically set to 0.1.

Initially, the weights are assigned random values and are then iteratively updated based on the observed data. Consequently, the predictions generated by a neural network incorporate an element of randomness. To account for this variability, the network is typically trained multiple times using different initializations, and the results are averaged. The determination of the number of hidden layers and the number of nodes in each hidden layer needs to be pre-determined. In a later section of this chapter, we will explore how these parameters can be selected through cross-validation Fig.2 elicits a snapshot of the code snippet used to implement Keras and TensorFlow.

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from tensorflow import keras

# Load the dataset
df = pd.read_csv("training.csv")

# Split the data into input (X) and output (y) variables
X = df.drop('prognosis', axis=1)
y = df['prognosis']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Define the neural network model
model = keras.Sequential([
    keras.layers.Dense(16, input_dim=132, activation='relu'),
    keras.layers.Dense(8, activation='relu'),
    keras.layers.Dense(41, activation='softmax')
])
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

# Train the neural network model
model.fit(X_train, pd.get_dummies(y_train), epochs=100)

# Evaluate the trained model
test_loss, test_acc = model.evaluate(X_test, pd.get_dummies(y_test))
print("Test Accuracy:", test_acc)

# Save the trained model
model.save("model.h5")
```

Figure 2.
Neural Network Code Snippet.

An epoch, within the context of neural networks, refers to a complete iteration through the entire training dataset during the model-training process. It involves utilizing the training data from the dataset to train the neural network, often in batches. As training progresses, the neural network adjusts its parameters to minimize the difference between the expected and actual output. The primary objective is to achieve optimal performance on the training data and ideally generalize well to new, unseen data.

The number of epochs is a critical hyperparameter in neural network training. Increasing the number of epochs may lead to improved training accuracy. However, it is important to be cautious as excessive epochs can potentially result in overfitting, where the model becomes too specialized to the training set and performs poorly on new data. In figure 3, the figure below indicates that the training process was executed for a total of 100 epochs.

```
123/123 [==============================] - 1s 1ms/step - loss: 3.4564 - accuracy: 0.1326
Epoch 2/100
123/123 [==============================] - 0s 1ms/step - loss: 2.5192 - accuracy: 0.3849
Epoch 3/100
123/123 [==============================] - 0s 1ms/step - loss: 1.4501 - accuracy: 0.7162
Epoch 4/100
123/123 [==============================] - 0s 1ms/step - loss: 0.7010 - accuracy: 0.9306
Epoch 5/100
123/123 [==============================] - 0s 1ms/step - loss: 0.3237 - accuracy: 0.9736
Epoch 6/100
123/123 [==============================] - 0s 1ms/step - loss: 0.1737 - accuracy: 0.9738
Epoch 7/100
123/123 [==============================] - 0s 1ms/step - loss: 0.0976 - accuracy: 0.9957
Epoch 8/100
123/123 [==============================] - 0s 1ms/step - loss: 0.0527 - accuracy: 0.9997
Epoch 9/100
123/123 [==============================] - 0s 1ms/step - loss: 0.0326 - accuracy: 1.0000
Epoch 10/100
123/123 [==============================] - 0s 1ms/step - loss: 0.0230 - accuracy: 1.0000
Epoch 11/100
123/123 [==============================] - 0s 1ms/step - loss: 0.0173 - accuracy: 1.0000
```

Figure 3.
Sample Epochs

4. Results and Discussion

The neural network algorithm employed to develop a medical virtual diagnosis system utilizing 132 symptoms and one target variable has yielded highly promising results. The accuracy of the model was reported at an impressive 95.6%, indicating a substantial level of success in predicting the diagnosis based on the provided symptoms. In this discussion, we will explore the implications and potential applications of these outstanding outcomes.

Achieving a 95.6% accuracy rate signifies that the neural network algorithm has demonstrated exceptional proficiency in accurately classifying medical conditions using symptom inputs. This high accuracy level suggests that the model has learned intricate patterns and relationships within the dataset, enabling it to make remarkably accurate predictions. This accomplishment opens up exciting possibilities for utilizing machine learning techniques in the healthcare industry.

The outstanding accuracy rate implies that the virtual diagnosis system developed using the neural network algorithm can provide valuable support to medical professionals. With such a high accuracy level, the model can effectively assist in diagnosing patients, potentially leading to improved patient outcomes and more efficient healthcare delivery. By leveraging the comprehensive set of 132 symptoms, the model offers a detailed and comprehensive analysis, enhancing the accuracy of the predictions.

However, it is important to acknowledge the potential limitations of the model despite its exceptional accuracy. Medical diagnosis involves complex and nuanced decision-making, taking into account various factors beyond symptoms alone. The model's reliance solely on symptom inputs may overlook other critical aspects, such as patient history, risk factors, and laboratory results. Therefore, while the virtual diagnosis system can provide valuable insights and predictions, it should be used as an adjunct tool to complement the expertise and judgment of medical professionals.

Furthermore, ensuring the reliability and consistency of symptom data remains a critical consideration. The inclusion of a large number of symptoms in the model provides a comprehensive foundation for diagnosis. However, standardizing symptom data collection across different patients and healthcare settings is crucial to ensure accurate predictions. Consistency in symptom reporting and accounting for individual variations in expressing symptoms can further enhance the reliability of the virtual diagnosis system.

The exceptional accuracy rate achieved by the model raises optimism about its real-world implications. Nevertheless, it is essential to assess the generalizability and scalability of the model to diverse patient populations and unseen data. Validation on independent datasets, evaluation of the model's robustness against variations in symptoms and patient demographics, and rigorous testing in real-world healthcare settings are necessary to ascertain its reliability and applicability.

The remarkable accuracy rate of 95.6% achieved by the neural network algorithm in the medical virtual diagnosis system using 132 symptoms and one target variable showcases its immense potential for assisting medical professionals and improving patient care. While the model's accuracy is highly promising, it is crucial to consider the limitations and complexities of medical diagnosis. The virtual diagnosis system should be regarded as a valuable tool to support healthcare professionals rather than a substitute for their expertise. Ongoing research, validation, and refinement will further enhance the model's performance, reliability, and practical application, driving advancements in the field of healthcare.

Yet, to improve the accuracy of the Neural Network algorithm, the following steps could be considered:

- Step 1: Increase the number of hidden layers: By adding more hidden layers to the neural network, its complexity increases, allowing it to potentially capture intricate non-linear relationships present in the data. This can enhance the model's ability to learn and make accurate predictions.
- Step 2: Explore different activation functions: Neural networks utilize activation functions to introduce nonlinearity into the model. Trying out different activation functions can help the neural network effectively capture complex patterns and relationships in the data. Each activation function has its own characteristics and may perform better for specific types of data or tasks.

5. Conclusion

Neural networks have gained significant attention and success in disease prediction due to their ability to handle complex and high-dimensional data. These models consist of interconnected layers of artificial neurons that mimic the structure and functioning of the human brain. The input layer receives various patient-related features, such as demographics, medical history, and symptoms, while the output layer generates predictions about the presence or risk of a specific disease.

The strength of neural networks lies in their ability to learn and recognize patterns from large datasets. Through a process known as training, the network adjusts the weights of its connections based on labelled data, optimizing its performance and improving its accuracy over time. This process involves minimizing the discrepancy between predicted and actual outcomes, typically using optimization algorithms like gradient descent.

Neural networks can effectively model complex relationships and interactions among different variables, which is crucial in disease prediction. They excel in capturing non-linear dependencies, such as the intricate interplay between genetic factors, lifestyle choices, and environmental influences. By leveraging their multi-layer structure and non-linear activation functions, neural networks can identify and extract relevant features from the input data, enabling accurate disease predictions.

However, the success of neural networks in disease prediction relies on the availability of high-quality and diverse datasets. Gathering comprehensive and labeled patient data, including clinical records, imaging data, and genetic information, is essential for training robust models. Furthermore, the performance of neural networks heavily depends on the quality of the input features and the representativeness of the training data.

One challenge in using neural networks for disease prediction is the interpretability of their predictions. The complex nature of these models often makes it difficult to understand the underlying reasoning behind their predictions. Research efforts are ongoing to develop techniques that enhance the interpretability of neural networks, allowing healthcare professionals to gain insights into the decision-making process of the model and increasing trust and acceptance in clinical settings.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Copyright:

References

[1] S. J. Trenfield *et al.*, "Advancing pharmacy and healthcare with virtual digital technologies," *Advanced Drug Delivery Reviews*, vol. 182, p. 114098, 2022.

[2] M. J. Iqbal *et al.*, "Clinical applications of artificial intelligence and machine learning in cancer diagnosis: Looking into the future," *Cancer cell international*, vol. 21, no. 1, pp. 1-11, 2021.

[3] M. D. Paranjpe, A. Taubes, and M. Sirota, "Insights into computational drug repurposing for neurodegenerative disease," *Trends in Pharmacological Sciences*, vol. 40, no. 8, pp. 565-576, 2019.

[4] D. Oliver, "David Oliver: lessons from the Babylon Health saga," *BMJ*, vol. 365, pp. 1-2, 2019. https://doi.org/10.1136/bmj.l2387

[5] F. Shi *et al.*, "Large-scale screening to distinguish between COVID-19 and community-acquired pneumonia using infection size-aware classification," *Physics in medicine & Biology*, vol. 66, no. 6, p. 065031, 2021. https://doi.org/10.1088/1361-6560/abe838

[6] H.-J. Jang and K.-O. Cho, "Applications of deep learning for the analysis of medical data," *Archives of Pharmacal Research*, vol. 42, no. 6, pp. 492-504, 2019.

[7] S. Ciranka, J. Linde-Domingo, I. Padezhki, C. Wicharz, C. M. Wu, and B. Spitzer, "Asymmetric reinforcement learning facilitates human inference of transitive relations," *Nature Human Behaviour*, vol. 6, no. 4, pp. 555-564, 2022.

[8] T. R. Gadekallu, N. Khare, S. Bhattacharya, S. Singh, P. K. R. Maddikunta, and G. Srivastava, "Deep neural networks to predict diabetic retinopathy," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1-14, 2023.

[9] R. Babukarthik, V. A. K. Adiga, G. Sambasivam, D. Chandramohan, and J. Amudhavel, "Prediction of COVID-19 using genetic deep learning convolutional neural network (GDCNN)," *Ieee Access*, vol. 8, pp. 177647-177666, 2020.

[10] F. Schwendicke, T. Golla, M. Dreher, and J. Krois, "Convolutional neural networks for dental image diagnostics: A scoping review," *Journal of Dentistry*, vol. 91, p. 103226, 2019.

[11] M. T. García-Ordás, J. A. Benítez-Andrades, I. García-Rodríguez, C. Benavides, and H. Alaiz-Moretón, "Detecting respiratory pathologies using convolutional neural networks and variational autoencoders for unbalancing data," *Sensors*, vol. 20, no. 4, p. 1214, 2020. https://doi.org/10.3390/s20041214

[12] M. Uzair and N. Jamil, "Effects of hidden layers on the efficiency of neural networks," in *2020 IEEE 23rd International Multitopic Conference (INMIC)*, 2020: IEEE, pp. 1-6.

[13] J. Gawlikowski *et al.*, "A survey of uncertainty in deep neural networks," *Artificial Intelligence Review*, vol. 56, no. Suppl 1, pp. 1513-1589, 2023. https://doi.org/10.48550/arXiv.2107.03342

[14] J. Wen *et al.*, "Convolutional neural networks for classification of Alzheimer's disease: Overview and reproducible evaluation," *Medical Image Analysis*, vol. 63, p. 101694, 2020. https://doi.org/10.1016/j.media.2020.101694

[15] A. Ashfaq, A. Sant'Anna, M. Lingman, and S. Nowaczyk, "Readmission prediction using deep learning on electronic health records," *Journal of Biomedical Informatics*, vol. 97, p. 103256, 2019. https://doi.org/10.1016/j.jbi.2019.103256

[16] J. Dong *et al.*, "Machine learning model for early prediction of acute kidney injury (AKI) in pediatric critical care," *Critical Care*, vol. 25, no. 1, p. 288, 2021. https://doi.org/10.1186/s13054-021-03724-0

[17] L. Ali, A. Rahman, A. Khan, M. Zhou, A. Javeed, and J. A. Khan, "An automated diagnostic system for heart disease prediction based on ${\chi^{2}} $ statistical model and optimally configured deep neural network," *Ieee Access*, vol. 7, pp. 34938-34945, 2019.

[18] Kaggle, "Find open datasets and machine learning projects, Kaggle," Retrieved: https://www.kaggle.com/datasets. [Accessed Jun. 04, 2023], 2023.

[19] F. J. J. Joseph, S. Nonsiri, and A. Monsakul, "Keras and TensorFlow: A hands-on experience," *Advanced Deep Learning for Engineers and Scientists: A Practical Approach*, pp. 85-111, 2021. https://doi.org/10.1007/978-3-030-66519-7_4