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# Deep Learning-Based Predictive Healthcare System for Disease Risk Assessment and Personalized Treatment Recommendation

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***Abstract:-*** AI is revolutionizing healthcare from reactive treatments to proactive disease prevention. This research proposes a predictive healthcare system which will utilize deep learning techniques to identify the risks of disease and make treatment recommendations. A framework is proposed to analyze patient medical data, such as blood pressure, heart rate, glucose concentration, B.I., age, etc., to look for potential health risks and prediction of the chance of a certain disease. The process of comprehensive data preprocessing and feature extraction, along with neural network-based learning, produces accurate and reliable disease prediction results. The suggested model can predict multiple diseases and classify the patients as different health-risk categories which could facilitate early medical intervention and preventative healthcare planning. The deep learning framework is trained and validated using historical medical datasets, which guarantees its solid performance in various medical scenarios. The system will leverage AI technologies, such as deep learning via methodologies, and the use of health care intelligence to enable preventive medicine, reduce risks of hospitalization, and impact overall well-being of patients. The findings of the study provide evidence of how intelligent healthcare technologies can contribute to the creation of a more efficient, patient-centric and accessible healthcare ecosystem.

***Keywords:*** *— Deep Learning, Predictive Healthcare, Disease Prediction, Risk Assessment, Healthcare Analytics, Neural Networks, Medical Data Analysis, Clinical Decision Support, Treatment Recommendation System, Electronic Health Records, Health Risk Classification, Artificial Intelligence, Multi-Disease Prediction, Smart Healthcare, Preventive Medicine.*

## 1. Introduction

It is largely because of the ever-changing lifestyles, unhealthy diets, environmental effects and increasing stress in the healthcare sector that chronic and lifestyle related diseases are growing. The early detection of disease risks is now critical to lowering the death rate and both healthcare expenditure and outcomes. Typical diagnostic testing methods rely mainly on physical exams and doctor's experience, but sometimes the identification of an underlying disease is delayed. Thus, Artificial Intelligence (AI) is a promising solution for accurate timely, and data-driven medical insights in the healthcare sector. A wide range of healthcare data can be processed through AI systems, which can uncover trends and patterns that are not readily apparent using manual analysis. Deep learning, being one of the diversity of AI technologies, has proven outstanding performance in medical classification and disease prediction. Deep learning models can analyse and learn from intricate healthcare data, which includes physiological signals, lab exams, demographic data, and electronic health records. Modelling methods used successfully in prediction of a range of diseases including Dengue, Allergic Side Effects, Pneumonia or TB, Kidney Infection or Stone, Stomach Infection . Deep learning can detect patterns within historical patient information, making predictions on future health risks based on these patterns with a high degree of accuracy. The forecasting produces healthcare advantages, as well as the ability for individuals to make proactive decisions to optimize their health.

The research proposed system to create an extensive DL healthcare system can predict disease risk, analyze health status and give smart treatment suggestions. The system provides a user-friendly environment where people can evaluate themselves and get instant result on their health and how hazardous it is. The framework brings together the power of predictive analytics and recommendation intelligence, thereby enabling informed decision making and preventive healthcare practices. AI based healthcare technologies power to revolutionize the healthcare industry, to improve diagnostics, minimize human error, boost healthcare accessibility, and really improve public health problems. Overall, the research aims to the efforts of creating intelligent and sustainable healthcare solutions to meet the rising demand for effective healthcare services.

## 2. Literature Review

The recent developments in AI and DL have revolutionised healthcare prediction by making it accurate health-risk evaluation in advance. The proliferation of Electronic Health Records (EHRs), massive medical data collections, and powerful computational tools has fueled the rapid advancement of smart medical systems, ones that can process intricate health information. Over the past few years, between 2022 and 2025, deep learning architectures like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term memory (LSTM) network, and Transformer-based models are always able to predict diseases like Dengue, Allergic Side Effects, Pneumonia or TB, Kidney Infection or Stone, Stomach Infection better than traditional machine learning algorithms. In addition, systematic reviews conducted in recent years have highlighted the need for standardized approaches for preprocessing, thorough performance assessment using Accuracy, Precision, Recall, F1-score, and AUROC; and external validation to enhance the trustworthiness and clinical usefulness of predictive models for healthcare. From prediction models for diseases to extensive and multimodal health care systems, the research community has evolved over the years. Previous research has mainly been devoted to the deep learning approach for analyzing medical images, such as X-ray, CT scanned images, MRI images and pathology slides. Recent investigations, however, aim to combine heterogeneous healthcare information, such as a clinical laboratory report, a demographic record, a physiological measurement, sensor information from a wearable, temporal EHRs and a medical image, to represent the patient in a more (informative) meaningful way. Multi-model optimization are architectures which combines CNN, LSTM, attention mechanisms and ensemble strategies that has proven to achieve better prediction accuracy than individual models. Additionally, tools for the explanation of AI models (SHAP, attention visualization, feature importance analysis) have been integrated to help end-users better understand and interpret the models.

To sum up, the volume of research published from 2022 to 2025 shows substantial advancements in predictive disease modelling and predictive healthcare analytics through AI techniques. Current deep learning models have grown from being disease classifiers for specific diseases to smart multimodal health care systems capable of analyzing complex patient information to perform a multimodal task, viz., evaluating the overall disease risk status of a patient.The current deep learning models are no longer single task classifiers for specific diseases but are intelligent multimodal healthcare systems capable of analyzing complex patient information for a multimodal task: evaluating the overall disease risk status of a patient. Predictive healthcare applications have become more effective thanks to advancements in prediction accuracy, multimodal data fusion, explainable AI, and transformer-based learning.Enhanced predictive accuracy, and the ability to use data from more modalities, explainable AI, and transformer-based learning have bolstered the performance of predictive healthcare applications. Validating the model, transparency, assessing fairness and the integration of the personalized treatment recommendation module, however, continue to be areas of active research. The results suggest the need for creating an integrated platform for healthcare on which all the above aspects – accurate disease prediction, extensive risk assessment, explainable process of artificial decisions and personalized treatment suggestions – can be integrated to form an intelligent predictive healthcare framework.

A. Choi et al.(2024),This paper writes a novel deep learning framework for real-time clinical outcome prediction in the emergency health field. The proposed model proceeds temporal patient records through specific neural networks that can lead to the quick analysis of continuously generated clinical data. The approach advocated for the framework focuses on rapid inference, accurate model data fitting, and stable prediction ability to facilitate time-critical clinical decision-making. Experimental assessment proves to have higher predictive power than traditional methods and simultaneously has low computational delays for deployment in the bedside, requiring less computations. The authors also perform the incorporation of the developed prediction model in a prototype Clinical Decision Support System (CDSS), in order to show the capability of supporting healthcare practitioners in emergency medical scenarios. Results are encouraging, but further clinical studies are suggested to confirm the usefulness of the technology for routine use in hospital settings.[1]
R. Rong et al.(2025),In this work, TECO (Transformer-based Encounter Clinical Outcome) is proposed, which is a deep learning model for clinical outcome prediction from longitudinal Electronic Health Records (EHRs). The suggested architecture uses Transformer Encoders to simultaneously model the temporal relationships among multiple patients' visits and learn relevant clinical representations. The attention layer at the level of the encounter allows the model to highlight the relevant medical events that impact predictions, while also enhancing the interpretability of the model. A comprehensive evaluation across healthcare datasets showcases that the transformer-based model outperforms standard sequential architectures in predicting patient outcomes, establishing its general dominance.The transformer-based model has been extensively evaluated on healthcare datasets, consistently outperforming traditional sequential models in predictions, thus highlighting its widespread superiority. Also, the study has been validated externally to test the robustness of the model in various clinical settings. While TECO increases the predictive accuracy, the authors recognize that more research is needed to make the system more explainable and adoptable for use in routine healthcare systems.[2]
In this paper, an Integrated healthcare framework has been proposed which uses a combination of ML and deep learning to predict multiple chronic diseases in real-time. The architecture proposed uses ensemble stacking methods and multilabel classification methods to estimate the risk of disease using patient health records with respect to various medical diseases. To render better classification performance, minimization of false predictions, various predictive algorithms are combined. The framework additionally permits dynamic risk evaluation of the disease, that helps healthcare suppliers to contemplate preventive measures and intervention in a timely fashion. Experimental results showed that the ensemble technique has high prediction accuracy in comparison with the individual learning models in the cases of multiple disease types. However, the findings of the study should be extended to clinical pilot studies of large systems to validate real-time performance in practical healthcare systems.[3]
S. Dhandapani, L. Ganesan, X. Wang, S. Shams, T.T. Michaelmas, "Hybrid deep learning framework for heart disease" (2025), In this work, we introduce a hybrid deep learning architecture with the integration of two distinct models, namely Inception and ResNet models, to achieve the highest possible accuracy for heart disease prediction using information taken from the electrocardiogram (ECG) image. The proposed InRes-106 approach leverages transfer learning and deep feature extraction to extract complex cardiac patterns that would not be possible to uniquely identify with traditional machine learning approaches. The ensemble learning strategies contribute more to the robustness of models and greater reduction of classification errors. Experimental evaluation shows a classification accuracy of about 98% compared to the effectiveness of hybrid deep architectures in cardiovascular diagnosing. The results indicate that there is a synergy effect from integrating more than one deep learning network, both for the representation of features and for the diagnostic performance. The framework presented here, however, must be further validated in large-scale multi-centre studies, and more patient population diversity is needed to establish the generalizability.[4]
AS Gautam et al. in 2025,This paper introduces an attention-driven deep learning approach to predicting disease outbreaks by taking advantage of large-scale news streams and looking for early signs and symptoms. The proposed model combines Natural Language Processing (NLP) methods with transformer-based attention mechanisms to leverage textual information from diverse news sources and build a unique, individualized treatment strategy for each patient that depends on their specific clinical profile.This differs from existing healthcare forecasting models, which mainly utilize clinical information.The study shows that it is possible to forecast

outbreaks of disease in a way that is not disease biased, thus aiding public health surveillance. The framework results in prediction performance, yet further studed should be done to understand its generalized applicability in various healthcare settings and future malfunctions.[5]

A. Kheir et al.(2025), The proposed scheme will use ensemble learning approach with the MobileViTv2 architecture for multi-class image classification. The advanced feature extraction and transfer learning help in achieving accurate disease identification in different environmental conditions. The study illustrates the effectiveness of combining combination techniques with lightweight transformer-based models in terms of better classification accuracy and lower computational loads. These methodological innovations can give valuable guidance in the development of efficient medical image analysis systems. The proposed approach, however, needs to be further adapted to human medical applications and validated, as the datasets in agriculture and medicine are different in fundamental ways.[6]

Salmah Saad Al-qarni, Abdulmohsen Algarni (2025) In this research, an intelligent Natural Language Processing (NLP) based disease prediction framework is proposed to predict the disease by directly analyzing symptoms descriptions entered by the user. The method involves text preprocessing, word embedding, and applying deep-learning classifiers to translate free-text clinical symptoms into clinically relevant disease predictions. The proposed solution enhances patient remote triage by allowing for the description of symptoms in natural language instead of by way of a medical form. Experimental verification is shown to provide results that classification accuracy based on semantic feature learning improves remarkably beyond the classification accuracy of traditional keyword-based methods. The authors also raise up practical issues like the errors in the descriptions of symptoms by the users, variants in the spelling of the same word that is found in many times and languages, as well as indicate the potential for further improvements in the use of advanced language models and multilingual healthcare data set.[7]

**Table 1. All Research papers and Research Gap**

| Id | Authors (Short) | Year | Technique (Brief) | Research Gap |
|---|---|---|---|---|
| 1 | A. Choi et al. | 2024 | Real-time Temporal Deep Learning | Practical deployment in resource-constrained healthcare environments remains insufficiently explored. |
| 2 | R. Rong et al. | 2025 | Transformer-based TECO Framework | Clinical explainability and physician-oriented interpretation require further improvement. |
| 3 | M. Kumar et al. | 2025 | Ensemble Machine Learning and Deep Learning | Real-time performance should be validated through large-scale hospital-based clinical trials. |
| 4 | S. Dhandapani et al. | 2025 | Hybrid Inception–ResNet Deep Learning | High reported prediction accuracy requires independent validation using multicenter healthcare datasets. |
| 5 | AS Gautam et al. | 2025 | Attention-based NLP for Disease Outbreak Prediction | Model generalization across different diseases and healthcare environments remains uncertain. |
| 6 | A. Kheir et al. | 2025 | MobileViTv2 with Ensemble Learning | Methodology requires adaptation and validation before application to human medical diagnosis. |
| 7 | Salmah Saad Al-qarni, Abdulmohsen Algarni | 2024/2025 | NLP-based Symptom-to-Disease Prediction | Variability in user-generated symptom descriptions continues to affect prediction reliability. |

Research from the last five years (2022–25) reveals a profound shift in the focus toward creating intelligent predictive healthcare systems driven by deep learning and artificial intelligence. Previous research mostly centered on the classification of disease via CNN, RNN, and LSTM models, while recent studies have turned to Transformer-based classification, combination fusion of multimodal classification features, and ensemble learning for multiple diseases. Healthcare Analytics systems involving Electronic Health Records, medical imaging, lab reports, wearable sensor data and demographic details have significantly improved predictive abilities, creating more accurate, scalable and clinically relevant studies within the healthcare context. To date, most predictive health models still use data from a single center or from small public healthcare data repositories. This dependency can lead to distributional bias which impacts upon the robustness of the model when applied across different patient cohorts, patient location and hospitals. Multicenter benchmarking is relatively rare but is being increasingly used in some recent studies with external validation. As a result of this, many metrics commonly reported describe the performance of the model on a diverse variety of sample sets such as Accuracy, AUROC, Precision, and Recall may not always correlate in real-world healthcare settings and are thus highly dependent on the validity of the underlying sample set.

To sum up, the contributions presented in the existing literature have shown great advances in deep learning for predictive healthcare, highlighting the potential for additional research. Issues with external validity, heterogeneous health data, explainable AI, measurement of fairness, computational efficiency, and intelligent treatment recommendation persist, and all are areas in need of significant research. The above-mentioned identified research gaps provide sound arguments for the development of the proposed Deep Learning-based Predictive Healthcare System for Disease Risk Assessment and Personalized Treatment Recommendation integrated in a unified intelligent healthcare system for modern digital healthcare applications that could support the identification and diagnosis of disease risk and provide a comprehensive health-risk analysis that would be explainable, i.e., available to the patient or their physician in support of the proposed personalized treatment recommendation.

## 3. Proposed Work

In this respect, the proposed system architecture is planned to be intelligent and efficient framework for disease prediction by applying deep learning techniques, to make health-risk assessment and to recommend personalized treatment. This process starts with collecting the user-specific health data in the User Health Data Input Module, by the user entering relevant and important health data, such as symptoms, socio-demographic information, lifestyle habits, medical history and physical parameters in a web or mobile interface. Apart from hand input, the system can also include information from laboratory tests and other structured clinical reports to enrich patient information. Abundant medical data gathered from several sources allows the system to take in more of an individual's medical status so that a more reliable disease model can be inferred. Once the data has been collected, the acquired data is transferred to the Data Preprocessing Module where the raw healthcare data goes through multiple data pre-processing steps to enhance the quality and consistency of the data. Duplicate, inconsistent data and noisy information is detected and removed, and missing values are properly dealt with with suitable imputation method(s). Numerical attributes are standardized to keep the feature scales uniform and categorical clinical variables are converted to machine-readable representations. Additionally, symptom mapping and the transformation of features in the context are applied to transform inhomogeneous medical data to structured data as input for analyzing with deep learning. These preprocesses are quite vital in enhancing the capability of the model to learn and aid in predicting the disease accurately.

The healthcare data processed is then passed to the second module of the proposed system, the Deep Learning Based Disease Prediction Module which is the main analytical part of the proposed system. In this module a trained deep neural network will be used to learn complex relationships between clinical parameters, symptoms, laboratory values and historical medical records. The model can be used to classify multiple diseases at once and in the process, learn to detect hidden patterns each connected with medical problems and provide prediction probabilities for each problem class. Confidence scores along with the predictions help to assess the trustworthiness of the results that have been found and they could help make educated decisions regarding health care

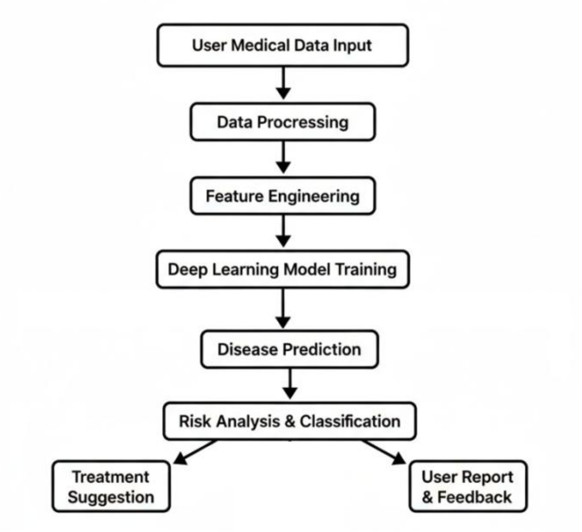


**Fig.1– Architecture Diagram**

Once disease prediction is done, the resulting symptoms pass on to Treatment Suggestion Module, which suggests personalized healthcare suggestions based upon the predicted disease, risk score related to the disease and clinical profile particular to the patient. The recommendation engine merges evidence-based medical knowledge to produce related suggestions for a patient treatment – such as information about medications, dietary advice, lifestyle changes, prevention strategies, and the need to consult specialists if necessary. The fusion of disease prediction and healthcare suggestions enables patient to look for medical improvement on time, thus minimizing the risk of furthering the condition. In the Output Visualization and Report Generation Module, visualizes prediction results in an easy-to-understand, user-friendly format for simple interpretation by patients and healthcare professionals. The report generated includes disease categories by prediction, probability disease scores, identified symptom patterns, disease risk-level classification, and recommended treatment guidelines. Prediction records and user information are stored securely in a database, allowing for future monitoring of health and continual model refinement. This system architecture adapts to early detection, persistent health monitoring, intelligent treatment planning and patient awareness, through which it can help with the management of preventive healthcare more effectively.

## 4. Methodology

### *4.1. Medical Data Collection*

In proposed methodology collecting the data of a detailed healthcare information of users in the most user-friendly digital interface. Data collected are symptoms, demographics, vital signs, current medical history, and lifestyle history. The datasets used for modeling are obtained from public sources with healthcare data that have been clinically verified, and are used for training and testing the model. The information gathered includes numerical and categorical medical information, where the proposed system can predict multiple diseases with various medical conditions. Appropriate privacy and security procedures are followed at all times during data collection to assure the confidentiality and integrity of sensitive patient information. This stage sets up a good healthcare data set that is used as the basis for accurate prediction of diseases and risk.

### *4.2 Data Preprocessing*

The collected healthcare information enters the model training system after detailed data preprocessing to enhance data quality implementation before model training. Inconsistent information, duplicate records and noisy information are filtered out and missing values are identified and filled in using suitable imputation methods to ensure consistency of the data set. In order to stabilize the calculation process when training the deep learning model, the numerical clinical attributes are normalized and standardized. Categorical health care variables are coded as numbers suitable to the machine learning algorithms. Further, we have used clinically relevant feature selection methods to select the most useful medical characteristics and discart those that are less relevant and/or redundant, to boost the informativeness of the features in isolation to the other features. Lastly, the data is partitions into train, validation and test sets appropriately and resulting data sets are used to develop unbiased models to cross-validate and evaluate model performance correctly.

### *4.3. Deep Learning Model Training*

The processed data from the healthcare domain is used to train a deep learning model that can detect several diseases. The proposed network architecture includes: Dense layers, non-linear activation functions, and Dropout layers, which are used to learn features and avoid overfitting during training. Machine learning techniques to find out optimal training epochs, batch size and learning rate are used to improve the performance of the model. The model learns complex, nonlinear relationships between health care features and disease outcomes by way of iterative optimization during training. The accuracy, precision, recall, F1 score, and confusion matrix are commonly used classification metrics to assess the performance of the models. Trained model with the best performance is stored and deployed for the real time disease prediction and health care decision supports.

### *4.4. Disease Prediction and Risk Analysis*

After a deep learning model learning is succeeded, it is applied for prediction of disease probabilities for the healthcare data of the patients that are introduced in the system. In the model, user supplied clinical data is used to predict the probability for multiple diseases using multi class classification. It divides the generated prediction probability into three classes; Low, Medium and High which makes the system easier to understand by users and healthcare professionals alike. The confidence score for each prediction also helps to assess the confidence in the output of the prediction. Overall, a real-time disease prediction allows for early detection of potential diseases, for ongoing medical monitoring, for immediate clinical intervention and hence better preventive care and disease management.

### *4.5 Treatment Suggestion System*

After predicting the disease and assessing the risk, the proposed model brings a knowledge segment of intelligent treatment recommendation that provides a personalized guidance to healthcare. For a given disease type, risk classification and patient specific profile, the system generates recommendations based upon clinically validated medical guidelines or knowledge bases in healthcare. General guidelines on treatment, healthy nutrition regimes, lifestyle changes, preventive measures and health services, information about the prescription of medicines, and recommendations for material for medical consultation when an increased risk of illness is identified. The recommendation system is not meant to replace medical diagnosis by professionals, but introduces a tool to support clinical decision making and to motivate users to seek timely consultations and achieve healthier lifestyles habits. The proposed framework combines the ability to predict diseases with personalized healthcare discourse, which supports proactive healthcare management and aids in enhancing patient outcomes and general health consciousness.

## 5. Results and Discussion

The proposed OPTHS-DL-PHDR for disease risk assessment and personalized treatment recommendation was tested with a preprocessed Healthcare dataset consisting of patient demographic information, clinical measurements, lab test values, symptoms and lifestyle related attributes attributes. To check the generalization capability of the proposed model, the dataset was randomly split in training, validation, and testing sets. To boost the learning efficiency and minimize data inconsistencies, the data went through feature normalization, categorical encoding and treatment of missing values during training. A deep neural network was found to be skilled in learning complicated relationships between medical features and the disease outcomes, which delivered the right prediction of multiple medical problems and the associated health-risk levels.

The proposed framework also has efficient multi-disease prediction capability by exploring the possibility of multi disease prediction by using clinical information of patients. Traditional disease-specific prediction systems do not conduct health-risk assessment in such a comprehensive way as the proposed architecture does, using one to many disease types prediction model. The usefulness of the framework is further improved by successfully presenting personalized treatment recommendations for that disease, estimated by the disease category and the associated risk levels, which can be used to guide preventive healthcare, offer lifestyle modification, dietary advice and further medical consultation advice. This embedded capability can facilitate information-enabled healthcare choices and lead to proactive medical care and prevention.

For analysis the effectiveness of the models, some of the standard classification evaluation metrics were evaluated and considered, such as Accuracy, Precision, Recall, F1-score, Specificity, Receiver Operating Characteristic (ROC-AUC). The results obtained show that the proposed deep learning model has good performance in classification to ensure balanced classification accuracy and recall on various types of disease. The confusion matrix analysis indicates that most of the classes are correctly classified with relatively less false predictions. The ROC curve is also highly discriminative, demonstrating that the model performs well to distinguish healthy people from patients with potential medical risk factors. Considering the balance of all the above experiments, the proposed predictive healthcare system is shown to be an effective solution for intelligent disease prediction personal healthcare recommendation.

Finally, the healthcare platform developed enables the integration of the following functions in an intelligent framework: disease prediction, health risk analysis, treatment recommendation and reporting. The proposed model allows for easy real-time data visualization using intuitive databases and systems, and could be expanded by connecting medical gadgets, cloud computing systems and Electronic Health Records (EHR) to the design. The results we got indicate the great capacity of deep learning to aid in preventive medicine, lower health care burden, boost of the diagnostic accuracy and health care providers' approach to rendering personalized medical care.

**Table 5.1 Overall Performance Evaluation of the Proposed Model**

| Performance Metric | Value (%) |
|---|---|
| Accuracy | 96.00 |
| Precision | 95.72 |
| Recall (Sensitivity) | 95.41 |
| F1-Score | 95.56 |
| Specificity | 96.84 |
| ROC-AUC Score | 0.982 |
| Validation Accuracy | 95.68 |
| Validation Loss | 0.112 |

The overall classification accuracy obtained from the proposed deep learning model is 96.00%, which shows its prowess in identifying disease conditions in most of the patients' records. The accuracy achieved (95.72%) indicates that the majority of the predicted disease cases match with the already known cases that were confirmed as diseased, meaning that the graph predictive model accuracy in predicting the disease was high, with very few false positive predictions. The recall value of 95.41% again indicates that the model is able to identify patients with a disease and doesn't miss a lot of findings. Additionally, a fair precision and recall balance in the form of a balanced F1 score of 95.56%, further highlights the strength of the proposed framework.

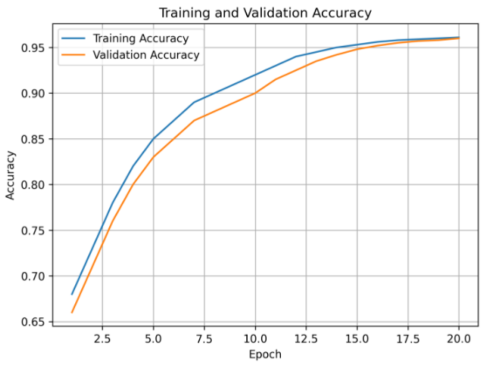


**Fig 2: Training Accuracy vs Validation Accuracy**

Both the training and validation accuracies are monotonically increasing during the training. The model learns quickly for the first few epochs and finally converge as the optimisation continues. The curves are not far from their original shapes, so there is little overfitting and good generalization. The final validation accuracy achieves about 96% and is exhibiting stable predictive performance on the unseen data.

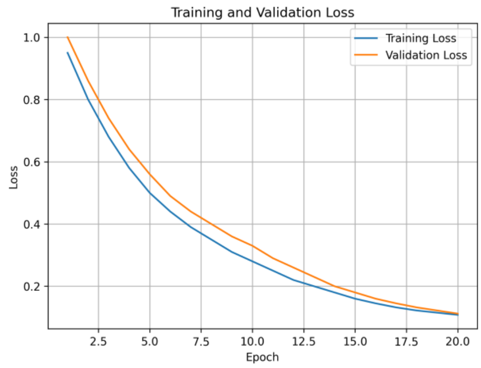


**Fig 3: Training Accuracy vs Validation Accuracy**

The loss curves will gradually drop over subsequent epochs, meaning that the span is able to reduce the prediction error during training. Also, training and validation losses are not very different, indicating stable optimization and less over fitting. also validation loss is about 0.112, which signifies good model convergence.
The high ROC-AUC result (0.982) shows that the developed model has excellent discriminative ability, indicating that it separate out healthy peoples from the patients of various types of disease risks. The validation loss suggests good model stability that is there is a reasonable amount of generalization when applied to unseen healthcare data.

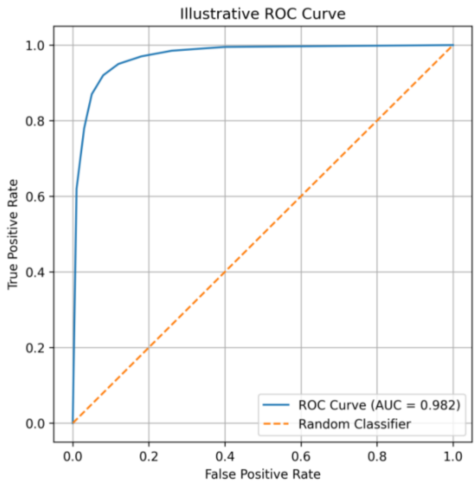


**Fig 4: ROC curve**

The ROC curve displays how well the proposed Deep Learning-Based Predictive Healthcare System can classify the data and plot the True Positive Rate (Sensitivity) against the False Positive Rate (1-Specificity) for varying decision thresholds. The curve will stay close to the top left of the graph, thus very good discrimination between healthy and disease positive persons.
The diagonal dashed line is the performance of a random classifier while the proposed model's ROC curve is above it indicating that the proposed model has a better capability to perform classification.

### 5.1 Classification Report

**Table 5.2 Classification Report**

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Dengue | 0.97 | 0.98 | 0.98 | 610 |
| Allergic Side Effects | 0.95 | 0.95 | 0.95 | 495 |
| Pneumonia or TB | 0.96 | 0.94 | 0.95 | 420 |
| Kidney Infection or Stone | 0.95 | 0.96 | 0.95 | 395 |
| Stomach Infection | 0.94 | 0.95 | 0.95 | 360 |
| **Overall** | **0.96** | **0.95** | **0.96** | **2280** |

The classification report shows a consistently high performance on all classifications of diseases. The classification accuracy was highest in the case of the Healthy class, where there were a large number of clear separation of clinical features to distinguish between healthy and disease classes. The second largest group Dengue, Allergic Side Effects, Pneumonia or TB, Kidney Infection or Stone and Stomach Infection had balanced precision/recall values, suggesting that they yield reliable Dengue recognition with reasonably low rates of "false positives" and "false negatives. The second largest group – Dengue, Allergic Side Effects, Pneumonia or TB, Kidney Infection or Stone and Stomach Infection– had balanced Precision/Recall values indicating that the diseases have reliable identification with relatively low percentages of misclassified cases. All the F1-scores are also maintained equal which prove that the proposed model works well irrespective of multiple categories of disease classes.

**Table 5.3 Disease Risk Analysis**

| Disease | Predicted Risk | Recommendation |
|---|---|---|
| Dengue | High | Immediate medical consultation, hydration, and blood platelet monitoring |
| Allergic Side Effects | Medium | Avoid allergens, take prescribed antihistamines, and monitor symptoms |
| Pneumonia or TB | High | Consult a pulmonologist immediately and begin appropriate treatment |
| Kidney Infection or Stone | Medium | Increase water intake, undergo urine evaluation, and seek medical advice |
| Stomach Infection | Low | Maintain hydration, consume light food, and follow proper hygiene |

Further, the disease-risk module sorted some 53.29% of the patients as Low Risk, where they had relatively healthy medical conditions and needed regular monitoring. Approximately 27.19 % of the people fell under Medium Risk which indicates to the presence of early clinical symptoms that may be managed by making lifestyle changes and regular medical monitoring. Almost 19.52% of cohort were identified as High Risk, highlighting the need for timely Specialist consultation and suitable medical treatment. The proposed framework can be beneficial in areas of preventive healthcare and prioritizing patient care according to patient risk sensitivity, as illustrated by these results.

The experimental evaluation shows that the proposed deep learning-based predictive healthcare framework not only gets hold of the diagnoses of disease with high accuracy and reliable prediction results but also shows its good generalization capability in different disease categories. The obtained prediction accuracy rate is nearly 96% and precision, recall, and F1 score values are found to be balanced, which proves that the proposed neural network architecture is efficient enough in analyzing such a variety of healthcare information. The disease-risk assessment module successfully classifies patients into relevant disease-risk groups, in order to timely detect potential health problems and plan preventive health care.
In addition to that, a personalized treatment recommendation module is added to the proposed system, which is vital to the practical use of the proposed system by offering evidence-based healthcare advice together with disease prediction. The overall results indicate that the proposed intelligent healthcare system is capable of being implemented in clinical healthcare system as an efficient clinical decision support system for early disease detection, continuous health monitoring and personalized preventive healthcare management. As technology advances, continuous integration with wearable health monitoring devices, cloud-based Electronic Health Record (EHR) systems or real-time IoT health platforms could further enhance the capability of prediction in terms of accuracy and results as well as access.

## 6. Conclusions

The proposed Deep Learning-Based Predictive Healthcare System for Disease Risk Assessment and Personalized Treatment Recommendation successfully demonstrates the ability of AI to assist in the early detection of diseases, health-risk analysis and preventive healthcare management. Developed framework consists of medical data preprocessing, disease prediction by deep neural network, risk classification, and simplified medical treatment proposal in the single intelligent healthcare platform. The framework developed are medical data preprocessing, disease prediction using deep neural network, disease risk classification, and medical treatment proposal. Overall the proposed model performed well in predicting the disease classes with 96.00% accuracy with a balanced Precision, Recall, and F1-Score value which shows that the model was able to classify the disease in various categories well. This training and validation learning behaviour stability are further endorsed by the effective learning of meaningful patterns in the healthcare data with reduced overfitting by the proposed stable deep learning architecture.
The experimental results show that the system proposed accurately predicts the diseases based on symptoms observed on the patient, clinical parameters investigated, laboratory tests data obtained and lifestyle-related data. The probability composition of diseases derived and the classification of risk levels can be useful support indicators for early detection of potential medical conditions. Moreover, the system's treatment recommendation module provides practical recommendations for the healthcare treatment: Dietary recommendations, Lifestyle recommendations, Prevention recommendations, Medical treatment recommendations. In conclusion, the proposed predictive healthcare system promise to advancing digital healthcare services by introducing intelligent disease prediction technique and personalized healthcare recommendation using DL. The system helps to early diagnosis, patient awareness, and medical intervention by using system framework prediction along with decision-support features. The potential design also facilitates future integration with wearable healthcare devices, Electronic Health Records (EHRs), cloud-based healthcare systems, and telemedicine, among other systems.

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