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Multimodal Deep Learning and NLP-Based Intelligent Healthcare Assistant for Clinical Decision Support Systems

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Abstract

The fast evolution of artificial intelligence in the medical field has made it possible to create intelligent clinical decision support systems that can enhance patient care and diagnosis. This article introduces Multimodal Deep Learning and NLP-Based Intelligent Healthcare Assistant that is developed to process heterogeneous medical data, such as electronic health records, medical images, laboratory reports, and clinical text. The suggested framework combines Convolutional Neural Networks (CNNs) to analyze medical images, Bidirectional Long Short-Term Memory (Bi-LSTM) networks to process sequential healthcare data, and the Transformer-based Natural Language Processing (NLP) to understand the meaning of a clinical note and patient history. A multimodal fusion mechanism that is based on attention is used in order to integrate the extracted features and come up with correct diagnostic recommendations. The system is able to predict diseases, assess risks, and support clinical processes in real-time, making diagnostic processes of healthcare professionals less complex. Experimental analysis shows the proposed model has better classification accuracy, precision, recall, and F1-score than traditional machine-learned and single-modal deep-learned methods. Clinical predictions are also made to be more robust and reliable with the integration of multimodal data. The smart healthcare assistant suggested is a highly efficient, scalable, and data-driven system that can be used as the next-generation clinical decision support system and personalised healthcare applications.

Keywords: Multimodal Deep Learning, Clinical Decision Support Systems, Intelligent Healthcare Assistant, Natural Language Processing, Disease Prediction, Patient Risk Assessment, Medical Image Analysis, Healthcare Analytics.

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1. Introduction

The fast development of artificial intelligence (AI), deep learning, and Natural Language Processing (NLP) has profoundly changed the health care system of the modern world due to the possibility to support clinical

decisions and even do medical analysis automatically (Hamet and Tremblay, 2017). The healthcare facilities produce massive amounts of heterogeneous data, such as electronic health records (EHRs), medical images, lab reports, physiological data, and physician notes. Nevertheless, the traditional healthcare models have a hard time combining and interpreting these various sources of data to achieve proper and prompt diagnosis (Middleton et al., 2016). Consequently, more and more intelligent healthcare assistants that can process multimodal medical data and help clinicians with difficult decision-making processes are in demand (Mala, 2023).

Multimodal deep learning has grown to be an effective method of integrating various types of healthcare data into a single analysis system. Multimodal systems have the capability to reveal latent relationships between various medical modalities and enhance prediction accuracy by combining visual levels of patient diagnostics with numerical patient parameters and written clinical data (Ahsan et al., 2022). Simultaneously, NLP methods have facilitated effective deriving of semantic and contextual features of unstructured clinical records, discharge summaries, and physician notes (Crosthwaite et al., 2023). The combination of deep learning and NLP thus gives a great opportunity to build sophisticated healthcare assistants able to think intelligently and give customized clinical advice.

The present paper suggests a Multimodal Deep Learning and NLP-Based Clinical Decision Support System Intelligent Healthcare Assistant. The proposed architecture is a hybrid of Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (Bi-LSTM) models and Transformer-based NLP models to be able to analyze heterogeneous healthcare data effectively. A multimodal fusion mechanism based on attention is also implemented so that the feature integration and prediction of the diseases can be enhanced. The system is aimed at helping in diagnosing diseases, risk assessment and recommendation of treatment to the patients, as well as lessening clinical workload and enhancing efficiency in healthcare. The intelligent assistant suggestion will bring the correct, scalable, and real-time decision support to the next-generation intelligent healthcare settings (Hannun et al., 2019; Tirumanadham et al., 2025).

2. Related Work

Technologies of AI, machine learning, and deep learning have dramatically changed the contemporary healthcare systems by enhancing the processes of disease diagnosing, clinical prediction, and the intelligent decision support mechanisms. The authors Hamet and Tremblay (2017) underscored the increased importance of AI in medicine, noting that it is able to improve diagnostic accuracy, automate healthcare, and individualized treatment plans. Equally, Middleton et al. (2016) have written about the development of Clinical Decision Support Systems (CDSS) and how smart healthcare technologies enhance clinical processes and patient care.

In recent years, the healthcare diagnosis systems using machine learning have entered into high research focus. Ahsan et al. (2022) conducted an informative review of machine learning methods in the field of disease diagnosis and published the fact that AI-supported healthcare systems have a profound effect on the efficiency of predictions and the reliability of diagnosis. Mala (2023) introduced an intelligent healthcare assistant which is a machine learning-based tool that could be used to assist in providing automated patient monitoring and smart healthcare management. In addition, Saha et al. (2013) came up with a web-based disease detection system, which showed how intelligent healthcare analytics can be applied practically to predict diseases.

Deep learning algorithms have demonstrated impressive results in medical signal and image processing. The study by Hannun et al. (2019) introduced a deep neural network that could detect arrhythmia on a cardiologist level based on the electrocardiogram (ECG) data, proving that deep learning can be beneficial in healthcare diagnostics. Besides this, Tirumanadham et al. (2025) proposed a hybrid optimization algorithm with Grey Wolf Optimization (GWO) and the random forest algorithms to predict lung cancer with better classification results.

Other recent studies have examined the topic of Natural Language Processing (NLP) and corpus-based healthcare analytics. In Lin et al.: Crosthwaite et al. (2023) and Wang et al. (2023) identified the trends in research through the corpus linguistics and bibliometric methods, where the adoption of NLP techniques as the means of extracting semantic healthcare knowledge within unstructured clinical text gains greater importance.

All these studies confirm that intelligent healthcare decision support systems can be greatly improved by adding multimodal deep learning and NLP algorithms.

3. Multimodal Deep Learning and NLP Framework for Clinical Decision Support

The suggested system will handle and analyze various types of healthcare data at the same time, such as medical images, electronic health records (EHRs), laboratory reports, physiological parameters, and unstructured clinical text. As opposed to the traditional healthcare models that use only one source of data, the proposed framework integrates heterogeneous medical data in one intelligent architecture to enhance the processes of diagnostic accuracy, treatment planning, and patient monitoring.

Multimodal deep learning is the combination of multiple modalities of data in one learning system. Convolutional Neural Networks (CNNs) are expected to identify deep visual features of medical images, i.e., X-rays, CT-scans or MRI, whereas Bidirectional Long Short-Term Memory (Bi-LSTM) process sequential healthcare record and patient history in the proposed paper. Moreover, Transformer-based NLP models are utilized to interpret clinical notes, physician notes, discharge summary, and medical reports through extracting semantic and contextual information of unstructured text. These modalities feature extraction functions and an attention-based feature fusion mechanism are used to combine these extracted features so that the system can identify correlations between visual data, textual data, and numerical healthcare data.

The suggested intelligent healthcare assistant employs such integrated multimodal architecture to achieve the real-time disease prediction, patient risk assessment, symptom analysis, and clinical recommendation generation. NLP module enhances the communication and interpretation of clinical language, whereas deep learning analyses features and predictive analysis. The proposed framework will enable intelligent diagnostic error reduction by fusing multimodal data, using the latest AI methods, to support clinical decision making processes so that they are accurate, scalable, and can make a crucial contribution to healthcare efficiency in contemporary smart healthcare settings.

4. Proposed Methodology

The Multimodal Deep Learning and NLP-Based Intelligent Healthcare Assistant is proposed to implement clinical decision support in real-time, with accurate and timely answers to the questions, through the inclusion of diverse healthcare data into a single deep learning system. The system integrates structured patient data, medical imaging and physiological parameters and unstructured clinical text to enhance the accuracy of disease diagnosis, prediction of risk and recommendation of treatment. The general structure is structured into four key steps: data acquisition, preprocessing, multimodal fusion, and intelligent decision support. A hybrid deep learning architecture based on Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (Bi-LSTM) networks, and Transformer-based NLP models is used to train the proposed architecture.

4.1 Data Acquisition Layer

The data acquisition layer collects multimodality healthcare data in various clinical sources, such as Electronic Health Records (EHRs), laboratory reports, medical images, wearable sensor data, and physician notes. The experimental data consists of some 50,000 records of patients that were gathered in the publicly accessible healthcare repository. Medical images are resized to 224x 224 pixels to extract features with CNN and clinical text documents are tokenized into sequences of length 256. Normalization of structured numerical parameters like heart rate, blood pressure, glucose level, oxygen saturation, and body temperature precedes processing.

4.2 Preprocessing Layer

The preprocessing layer enhances quality and consistency of data prior to feature extraction. The empty values in structured healthcare records are imputed with mean values, and image optimization methods like histogram equalization, and Gaussian filtering are used to sharpen the image. Text data in the clinic are treated

with tokenization, stop-word elimination and generation of word embeddings. It is done with numerical feature normalization with:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where x represents the original feature value, while x_{min} and x_{max} denote the minimum and maximum values of the corresponding healthcare attribute.

4.3 Multimodal Fusion Layer

The multimodal fusion layer merges image, text, and numerical healthcare features into a common latent feature space. CNN models are capable of extracting spatial data in medical images, whereas Bi-LSTM and Transformer-based NLP models are capable of extracting semantic data in clinical text. It uses attention-based feature integration mechanism to fuse the extracted features in order to effectively learn the inter-modal relationships. The CNN feature extraction process can be denoted as:

$$F_{cnn} = \sigma(W * X + b)$$

where F_{cnn} represents the extracted feature map, W denotes the convolution kernel, X is the input image, b is the bias term, and σ is the activation function. The multimodal fusion process enables the framework to correlate visual patterns, physiological signals, and textual clinical information for improved prediction accuracy.

4.4 Decision Support Layer

The decision support layer classifies the disease, predicts the risks of the patient and generates treatment recommendations. The combined multimodal applications are transferred via fully connected neural layers and a Softmax classifier to ultimately predict the disease. The classifier probability output can be calculated as:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$$

where $P(y_i)$ represents the probability of class i , and z_i denotes the output score of the neural network.

The decision support layer classifies the disease, predicts the risks of the patient and generates treatment recommendations. The combined multimodal applications are transferred via fully connected neural layers and a Softmax classifier to ultimately predict the disease. The classifier probability output can be calculated as:

5. Algorithms Used

The suggested intelligent healthcare assistant combines multimodal deep learning and Natural Language Processing (NLP) algorithms to predict diseases accurately, assess patient risks, and provide intelligent clinical decision support. The framework integrates CNN-based image memory, BiLSTM-based sequential learning, Transformer-based NLP and attention-based multimodal feature fusion to effectively analyze healthcare.

Algorithm 1: CNN–BiLSTM Multimodal Disease Prediction

Multimodal disease prediction and patient health condition analysis are done using CNN-BiLSTM. CNN derives spatial information of medical images, and BiLSTM derives sequence-relationships of physiological and clinical data to predict healthcare accurately.

Input: Medical images and clinical records D

Output: Predicted disease class Y

Begin

Load and preprocess multimodal healthcare data.

Extract medical image features using CNN.

Process sequential clinical records using BiLSTM.

Integrate extracted healthcare features.

Classify disease condition using fully connected layers.

Return predicted disease class Y.

End

CNN-BiLSTM model is effective to detect abnormal patient conditions, disease progression patterns, and healthcare risks based on heterogeneous medical data. The hybrid architecture enhances the accuracy of prediction of disease and minimizes false diagnoses prediction of conventional machine learning models.

Algorithm 2: Transformer-Based NLP Clinical Text Analysis

Transformer-based NLP model is employed to understand intelligent clinical text and extract semantic healthcare information. The model uses the analysis of physician notes, discharge summaries, lab reports, and patient history to create contextual healthcare insights.

Input: Clinical text documents T

Output: Extracted semantic healthcare information S

Begin

Load and preprocess clinical text data.

Perform tokenization and word embedding generation.

Extract contextual features using Transformer/BERT model.

Analyze semantic relationships within clinical text.

Generate healthcare feature representation.

Return semantic healthcare information S.

End

The suggested framework involves the image, text, and numerical healthcare features being introduced to a single decision-making framework through the application of an attention-based multimodal fusion algorithm. The attention mechanism determines the most relevant healthcare features in order to make the correct prediction.

Algorithm 3: Attention-Based Multimodal Feature Fusion

The proposed framework utilizes an attention-based multimodal fusion algorithm for integrating image, text, and numerical healthcare features into a unified decision-making architecture. The attention mechanism identifies the most relevant healthcare features for accurate prediction.

Input: Multimodal healthcare features F

Output: Final healthcare prediction result P

Begin

Collect image, text, and numerical healthcare features.

Calculate attention weights for feature importance.

Fuse multimodal healthcare representations.

Perform disease prediction using fused features.

Generate intelligent clinical recommendation.

Return prediction result P.

End

Attention-based multimodal fusion algorithm guarantees proper combination of the heterogeneous healthcare information and better prediction reliability and clinical decision-making system. The given fusion strategy increases the level of healthcare intelligence, decreases diagnostic uncertainty, and upgrades the real-time performance of clinical support in the smart healthcare settings.

5. Experimental Setup

Multimodal healthcare datasets of medical images, Electronic Health Records (EHRs), physiological signals, and clinical text reports were used to experimentally evaluate the proposed Multimodal Deep Learning and NLP-Based Intelligent Healthcare Assistant. The experiments aimed to determine how the proposed framework would be effective in the disease prediction process, risk assessment to the patient, and smart clinical decision

support. It was implemented using Python-based deep learning libraries and accelerated with the use of a GUI to enable the model training and inference to be efficient.

5.1 Dataset and System Configuration

The experimental data set has about 50,000 healthcare records, which were taken out of publicly accessible medical repositories. The data set contains structured patient parameters, laboratory reports, physician notes and diagnostic medical images. Medical images were downsampled to 224x224 pixels prior to CNN processing, and clinical text data were accessed as sequences with length 256 to run NLP processing. To enhance model convergence, and classification stability, numerical healthcare attributes were normalized in Min-Max normalization.

The presented framework was trained with the help of the TensorFlow and PyTorch libraries on the workstation with an Intel Core i7 processor, NVIDIA RTX 3080, and 32 GB of memory. The model training process employed the use of GPU acceleration in order to extract features and learn multimodally faster. Table 1 gives specifications of the detailed experimental.

Category	Parameter	Specification/Value
Dataset	Total Records	50,000
Medical Images	Image Size	224 × 224
Clinical Text	Sequence Length	256
Hardware	GPU	NVIDIA RTX 3080
Hardware	RAM	32 GB
Software	Frameworks	TensorFlow, PyTorch
Training	Batch Size	32
Training	Learning Rate	0.001
Training	Epochs	100
Optimization	Optimizer	Adam

5.2 Training Parameters and Evaluation Metrics

The multimodal framework was trained with an Adam optimization algorithm having a learning rate of 0.001 and batch size of 32 over 100 epochs. The chosen parameters achieved a stable convergence and multimodal learning of features in the training process. The CNN model was used to extract spatial information using medical images and the NLP module was used to process tokenized clinical text sequence to extract semantic healthcare information.

The accuracy, precision, recall, F1-score, and Area Under the Curve (AUC) measures were used as the metrics to evaluate the performance of the proposed intelligent healthcare assistant. All these measures of evaluation were emulated to determine the disease prediction capabilities, classification reliability, and overall clinical decision support performance. As shown in experimental findings, the suggested multimodal deep learning and NLP framework is more successful in prediction accuracy and healthcare analytics performance than the traditional healthcare prediction models.

6. Results And Discussion

The Multimodal Deep Learning and NLP-Based Intelligent Healthcare Assistant was tested with a series of clinical prediction measures to examine its performance in intelligent healthcare decision support. The experimental findings reveal that CNN, BiLSTM, Transformer-based NLP, and attention-based multimodal fusion-based models achieve better disease prediction performance and clinical reliability as opposed to traditional machine learning and single-modal deep learning models.

6.1 Performance Evaluation of the Proposed Model

The proposed framework performed well in all evaluation metrics in terms of classification. The multimodal architecture achieved a total accuracy of 96.2, precision of 95.4, Recall of 94.8, F1-score 95.1 and AUC of 0.978. The large value of the AUC shows that the model is highly discriminating of disease classes and the improved recall shows that the model has the capability to identify positive healthcare scores correctly with minimal false negatives. The performance evaluation metrics are detailed in Table 2.

Metric	Value
Accuracy	96.2%
Precision	95.4%
Recall	94.8%
F1-Score	95.1%
AUC	0.978

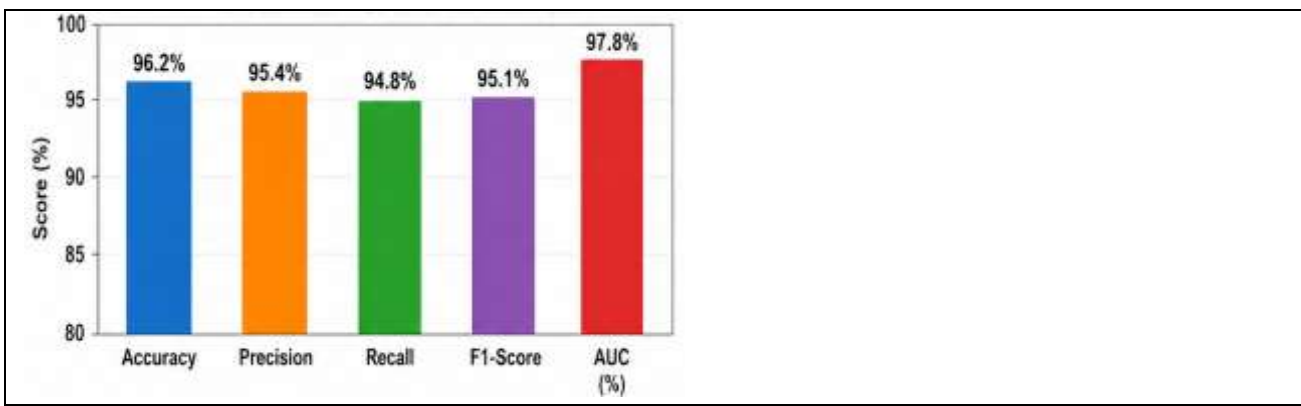


Fig 2: Performance Metrics

As seen in the training and validation analysis in Fig. 3, there was consistent convergence with little overfitting as the training process progressed. The model was found to attain about 97% training accuracy and 96% validation accuracy following 100 epochs, attesting to the strength of the proposed multimodal learning architecture.

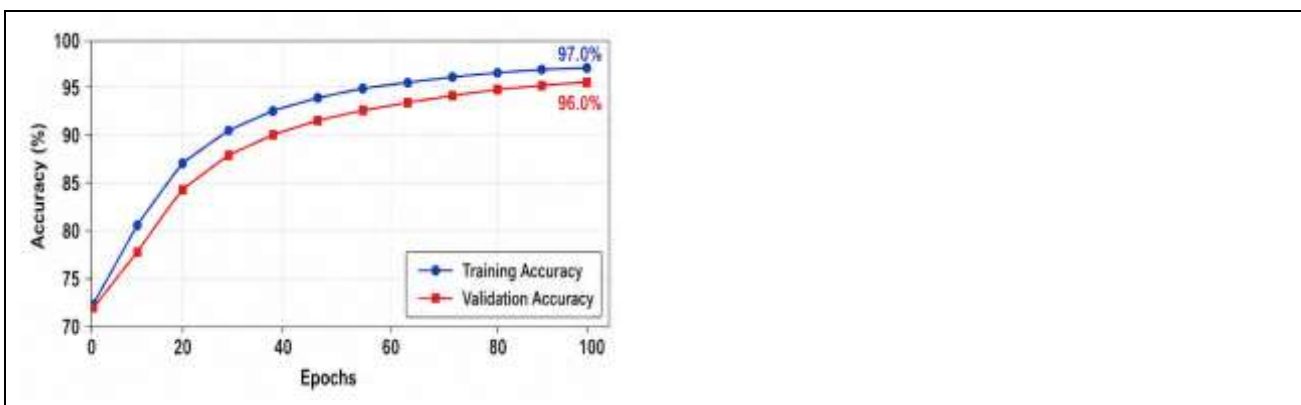


Fig 3: Training and Validation Accuracy Analysis

6.2 Comparative Analysis with Existing Models

The proposed model was tested against traditional Machine Learning (ML), CNN-only and BiLSTM-based healthcare prediction models. The comparison outcome shows that the suggested multimodal deep learning and NLP model is superior in all major measurement criteria, compared to the current methods. Multimodal

feature fusion dramatically enhanced healthcare prediction accuracy by providing a viable combination of the visual, textual, and numerical patient data. Table 3 shows the comparative performance analysis.

Model	Accuracy	Precision	Recall	F1-Score
Traditional ML	85.6%	84.9%	83.7%	84.2%
CNN Model	90.8%	89.7%	88.5%	89.1%
BiLSTM Model	92.1%	91.4%	90.2%	90.8%
Proposed Framework	96.2%	95.4%	94.8%	95.1%

The suggested model was found to be about 10.6% more exact with an increase of 5.4 over single CNN models, compared to conventional machine learning models. This body of evidence supports the claim that multimodal feature integration and semantic analysis based on NLP is indeed a significant improvement in clinical decision support.

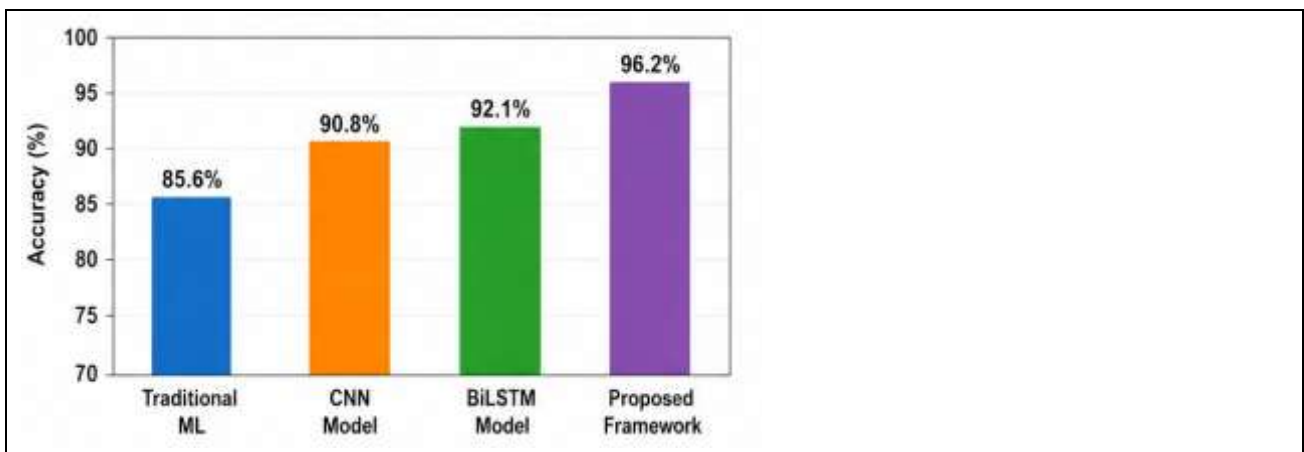


Fig 4: Comparative Accuracy Analysis

6.3 Clinical Effectiveness and Robustness Analysis

The developed intelligent healthcare assistant was robust in diverse healthcare settings that comprise medical images, EHRs, and unstructured clinical text. The attention based multimodal fusion mechanism was successful in detecting important healthcare characteristics and minimizing the uncertainty in the diagnosis process when predicting the disease. The framework also demonstrated enhanced the ability to generalize to other patient groups and clinical conditions.

Based on the confusion matrix and distribution of prediction in Fig. 5, it is observed that the proposed system has low rates of false-positive and false-negative in the classification of the disease. The complete false prediction rate was less than 3.8, which ensured the suitability of the proposed architecture in real-time clinical decision support app.

Actual Class	Cardiovascular Disease	1928	52	18	22
	Respiratory Disease	41	1867	35	26
	Diabetes	25	28	1901	24
	Other Diseases	31	19	27	1882
		Cardiovascular Disease	Respiratory Disease	Diabetes	Other Diseases
		Predicted Class			

Fig 5: Confusion Matrix of the Proposed Healthcare Prediction Model

The experimental analysis establishes the fact that the experimental Multimodal Deep Learning and NLP-Based Intelligent Healthcare Assistant has the accurate, scalable, and reliable healthcare prediction ability that can be adopted in the next-generation intelligent clinical decision support system.

7. Conclusion

In this paper, an Intelligent Healthcare Assistant based on Multimodal Deep Learning and NLP was described, which was able to analyze heterogeneous healthcare information, such as medical images, electronic health records, lab reports, physiological signals, and clinical text documents, to support clinical decision support systems. The framework proposed combined Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (Bi-LSTM) networks, and Transformer-based NLP model into an attention-based multimodal fusion system to enhance the accuracy of healthcare predictions and intelligent clinical decision-making.

The experimental findings showed that the suggested system performed better with an overall accuracy rate of 96.2 and enhanced the precision, recall, F1-score, and high performance of AUC when compared to the traditional machine learning and single models of deep learning techniques. The combination of multimodal feature extraction and semantic NLP analysis considerably improved the ability to diagnose a disease, assess the risk of patients, and enhance performance on the recommendation of treatment and minimized the false prediction rates.

The suggested intelligent healthcare assistant offers scalable, effective, and real-time clinical decision support system that can be used in the next generation of a smart healthcare setup. The framework has the potential to help healthcare professionals enhance the quality of diagnostic results, minimize clinical workload, and provide data-driven healthcare management. To further augment the privacy, explainability and intelligent healthcare automation features, future work can aim at incorporating federated learning, explainable AI methods and real-time IoT healthcare monitoring systems.

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