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Enhancing Telehealth: Multiple Disease Prediction Through Ensemble Approach

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Abstract: Telemedicine plays a pivotal role in extending healthcare reach through remote consultations, addressing gaps in underserved regions and offering convenience, especially during crises. Data mining techniques in telemedicine extract critical insights from complex medical data, enhancing early disease detection and personalized care. This study presents a novel approach that leverages two hybrid deep learning models (CNN-Bi-LSTM, CNN-GRU) and a stacking ensemble model to predict multiple diseases using telemedicine-derived features. The stacking ensemble utilizes Support Vector Machine (SVM) as its meta-learner. The dataset is sourced from the YBI Foundation's repository, and extensive experimentation showcases the ensemble's superiority, achieving 99.52% accuracy, 99.54% precision, 99.57% recall, and 99.54% F1-score. These remarkable results highlight the potential of unified model architectures in enhancing disease prediction using telemedicine. Beyond advancing predictive healthcare, this research demonstrates ensemble learning's effectiveness in intricate medical datasets, ultimately aiding clinical decisions and patient outcomes.

Keywords: *Convolutional Neural network, Data mining, Gated Recurrent Unit, Long short-term memory, Support vector machine, Telemedicine.*

1. Introduction

Telemedicine is a transformative healthcare approach that employs modern communication technologies to deliver medical services remotely. Without the requirement for in-person visits, people are able to speak with medical experts via telemedicine and obtain medical advice, and diagnosis [1]. This approach leverages digital tools such as video conferencing, phone calls, emails, and mobile apps to bridge geographical gaps and enhance access to healthcare, making it particularly valuable for individuals in remote or underserved areas. Telemedicine encompasses a wide range of medical services, from primary care and specialty consultations to mental health support and chronic disease management [2]. It not only offers convenience and cost-effectiveness but also plays a critical role in emergencies and situations where physical interactions are restrict.

The benefits of telemedicine extend beyond convenience. Patients can access medical expertise that might not be available locally, facilitating consultations with specialists and experts from around the world. Additionally, telemedicine enables continuous monitoring of patients with chronic conditions through wearable devices and remote sensors, enhancing their quality of life [3]. Despite its advantages, challenges exist, including the need for reliable internet connectivity, ensuring patient data privacy and security, navigating regulatory frameworks, and addressing diagnostic limitations that require physical examinations [4]. As technology continues to advance, telemedicine's potential to reshape healthcare delivery and improve patient outcomes remains substantial, fostering a more connected and accessible healthcare ecosystem.

Data mining techniques have a significant impact on the field of telemedicine by leveraging the abundant digital healthcare data generated through remote consultations, patient monitoring, and electronic health records [5]. These methods, including clustering [6], classification, and association rule mining, help telemedicine professionals identify patterns and correlations hidden within patient data. By grouping patients with similar profiles, categorizing based on symptoms, and uncovering relationships between medical parameters, practitioners can enhance patient care through targeted interventions and accurate diagnoses.

Predictive modelling [7] is another crucial technique that uses historical patient data to anticipate health risks, disease progression, and treatment responses. This proactive approach enables healthcare providers to optimize treatment plans and resource allocation effectively, while sentiment analysis techniques applied to patient interactions aid in gauging satisfaction, detecting emotions, and tailoring communication strategies.

In essence, data mining empowers telemedicine by extracting actionable insights from intricate healthcare data, resulting in improved diagnostic precision, predictive health outcomes, and personalized patient care. These techniques elevate the quality and accessibility of remote

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medical services, fostering a data-driven approach that advances the field of telemedicine.

1.1 Challenges in Traditional Models

Accurate disease prediction through traditional methods encounters a host of obstacles that can compromise their efficacy. One of the foremost challenges lies in their reliance on predetermined features, which might not encapsulate the entirety of relevant data patterns. This can result in the omission of critical information, undermining the precision of predictions. Moreover, the intricacies of many diseases often entail nonlinear relationships between variables, a complexity that traditional linear models struggle to capture. Consequently, these models may fail to grasp the nuanced interactions within the data, leading to less accurate forecasts.

Fig. 1. Data mining technique in telemedicine

Another hurdle arises from the high-dimensional nature of medical datasets [8]. The vast number of variables can overwhelm traditional methods, rendering them computationally taxing and susceptible to over fitting. The manual process of feature engineering demand substantial domain knowledge and time investment. This selection of pertinent features might introduce human biases or overlook important aspects of the data, further hindering the accuracy of disease predictions. Furthermore, the scalability of traditional methods is put to the test with the surge in dataset size, as the models can become sluggish in handling the increased volume, undermining their practicality in real-world healthcare settings [9].

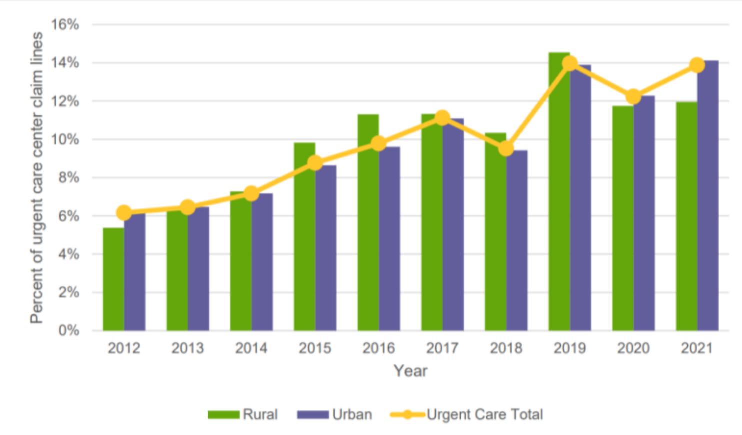

Fig. 2. Usage of rural, urban, urgent care users in telemedicine

The generalization capability of traditional models presents a challenge. Their simplicity can hinder their ability to adapt to variations in data distribution, making them less versatile in new patient populations or changing medical landscapes [10]. As the healthcare field continually evolves, the static nature of traditional methods becomes a limitation, as they might require constant updates or even replacement to remain relevant. Collectively, these challenges underscore the need for more advanced techniques, such as machine learning (ML) and deep learning (DL), which can surmount these limitations and offer more robust and accurate disease prediction frameworks [11].

The adoption of telemedicine is motivated by the desire to overcome geographical barriers, enhance healthcare accessibility, and improve patient experiences. By enabling remote consultations and medical services [12], telemedicine offers convenient access to healthcare expertise, particularly for individuals in underserved or remote areas. This approach minimizes travel burdens, saves time, and fosters timely medical advice and treatment. Furthermore, telemedicine supports continuous care for chronic conditions, extends specialist consultations globally, and has the potential to reduce healthcare costs by optimizing resource allocation. The recent emphasis on pandemic preparedness has further highlighted its role in ensuring healthcare continuity during emergencies. Overall, telemedicine aligns with technological trends, advancing healthcare by making it more patient-centric, efficient, and widely accessible [13].

1.2 Applications of Telemedicine

Telemedicine, a rapidly advancing field, enhances healthcare accessibility through remote consultations, benefiting underserved regions and reducing geographical constraints. It also improves healthcare delivery by enabling timely diagnosis, chronic disease management, and home health monitoring through remote assessments and specialist Access.

1.2.1 Remote Consultations

Remote consultations, a pivotal application of telemedicine, revolutionize the way patients access healthcare. Through digital platforms and video conferencing, individuals can securely connect with healthcare professionals from the comfort of their homes or workplaces. This approach not only eliminates the need for physical visits but also transcends geographical barriers, offering medical advice, diagnoses, treatment recommendations, and follow-up care regardless of location [14]. Remote consultations particularly benefit those in rural or underserved areas, individuals with mobility constraints, and patients seeking expert opinions from specialists outside their region. Furthermore, telemedicine's remote consultation services have proven invaluable during public health crises, enabling continuous medical support while minimizing the risk of viral transmission. This application encapsulates telemedicine's potential to enhance accessibility, patient-centered care, and healthcare delivery efficiency on a global scale.

1.2.2 Chronic Disease Management

Chronic Disease Management stands as a pivotal application of telemedicine, offering a transformative approach to caring for individuals with ongoing health conditions. Through remote monitoring and regular virtual interactions, telemedicine empowers patients to actively engage in their health management while healthcare providers remotely track and assess their progress. This application benefits patients with chronic diseases such as diabetes, heart disease, and respiratory conditions by facilitating personalized care plans, medication adjustments, and lifestyle guidance [15]. Continuous monitoring of vital signs, symptoms, and treatment responses enables early intervention, reducing the risk of complications and hospitalizations. Telemedicine's convenience and accessibility, coupled with the ability to transmit real-time health data, foster a proactive partnership between patients and healthcare professionals, ultimately improving the quality of life for those managing chronic condition.

1.2.3 Specialist Access

Specialist Access as an application of telemedicine refers to the capability of patients to remotely connect with medical specialists through digital platforms, enabling expert consultations and healthcare services regardless of geographical distances [16]. This innovative approach improves patients' access to specialized medical expertise, particularly beneficial for those in underserved areas or facing travel constraints. By leveraging telecommunication technologies, patients can receive timely diagnoses, treatment recommendations, and ongoing care from specialists, leading to more convenient and efficient healthcare delivery while minimizing the need for in-person visits.

1.2.4 Home Health Monitoring

Home Health Monitoring, a key application of telemedicine, involves the use of remote monitoring technologies to track patients' health conditions from the comfort of their homes. Through devices like wearable sensors, smart medical devices, and mobile apps, patients can collect and transmit essential health data such as vital signs, glucose levels, or medication adherence to healthcare providers in real time [17]. This enables proactive healthcare management, early detection of health issues, and personalized interventions, reducing the need for frequent clinic visits and hospitalizations while enhancing patients' quality of life and overall health outcomes.

In order to improve the precision of multi-disease prediction, this research introduces a stacking ensemble model that uses hybrid CNN-Bi-LSTM, CNN-GRU models coupled with a meta-learner -SVM [21]. The dataset is sourced from the YBI Foundation's repository. Patient data was collected, and the remedy for them was given according to the prediction of the ensemble model, ensuring personalized treatment plans. The combination of the two hybrid methods and the ensemble model together made accurate predictions, enhancing the precision of disease diagnosis and treatment recommendations. The model can predict multiple diseases using the data, allowing for early detection and proactive healthcare interventions to improve patient outcomes. The following sections provide an overview of the related works in

Section 2 and elaborate on the methods employed for disease prediction in Section 3. The findings and discussion are described in Section 4. Finally, Section 5 brings the conclusion.

2. Literature Review

Ahmed and colleagues [22] presented a robust telemedicine infrastructure featuring an up-to-date topology, strengthened by the processing of the MooM dataset and the implementation of the specialized TelMED protocol for transmitting medical data remotely. The infrastructure prioritizes an application-centric approach to Electronic Health Records (EHR) management through edge computation. The primary aim is to surpass the Quality of Service and Quality of Data achieved by conventional communication channel algorithms in processing medical data. The study showcases the efficacy of the proposed technique through MooM dataset processing and TelMED channel optimization, demonstrating enhanced efficiency in medical data handling. The resulting improvement, substantiated by comparisons of MooM datasets during reverse processing for diagnosis, underscores the potential for elevated Quality of service in the proposed infrastructure.

Salman et al [23]aimed to enhance telemedicine services by reducing waiting times for remote patients through a scalable model. The model, named Triaging and Prioritizing Model (TPM), focuses on real-time healthcare monitoring for chronic heart disease patients. By integrating hybrid algorithms that combine Evidence-Theory with Fuzzy Cluster Means (FCM), TPM triages and prioritizes patients, considering both remote and Emergency Department (ED) patients. The approach significantly reduces waiting times by accommodating a larger patient volume efficiently. The simulation, involving 580 chronic heart disease patients with varying emergency levels determined by vital data from sensors, showcases TPM's effectiveness in managing patient requests within 1,185 minutes, outperforming benchmark studies.

Katarya et al [24] served as a guide for selecting suitable tools and algorithms for effective analysis. It offers benefits to a wide range of stakeholders including policymakers, hospitals, patients, and pharmaceutical companies. It suggests the allocation of increased funds to domain experts to enable comprehensive patient health analysis and monitoring from home. Although reluctance to adopt Big Data Analytics (BDA) techniques often stems from organizational changes required, this paper aims to inspire adoption by presenting a compelling case for incorporating BDA within healthcare organizations, ultimately driving motivation for its implementation.

In their work Choi [25] introduced an extensive knowledge processing system for the healthcare industry, utilizing Hadoop's Map Reduce software to conduct association mining on big data. The approach efficiently manages health information by leveraging WebBot and a common data model to process heterogeneous data. By combining distributed processing and association mining, the proposed method utilizes MapReduce to extract and analyze chronic disease nomenclature from health big data. Through mapping and reducing processes, frequent item sets meeting support criteria are identified, generating association rules between datasets. This result in the creation of a knowledge base that support health management, offering real-time, semantically related insights into chronic diseases. Through the application of knowledge processing based on mining techniques, this approach elevates the technological worth and intelligent effectiveness within the healthcare domain, ultimately leading to advancements in health and overall well-being.

Heart disease linked to diabetes is a condition that impacts individuals with diabetes due to problems with insulin production and utilization. Arumugam et al [26] pointed out that despite the availability of various data mining classification algorithms for heart disease prediction, there's a lack of data for forecasting heart disease accurately in individuals. Furthermore, the speaker highlighted that they fine-tuned the decision tree model because it outperformed the naive Bayes and SVM models, aiming to improve its ability to forecast heart disease likelihood in diabetes patients.

Priyadharsan et al [27] employed ML algorithms to monitor human health conditions. Initial training and validation are conducted using the UCI dataset, while the testing phase utilizes an IoT setup to collect heart rate, blood pressure, and temperature data. This phase predicts health abnormalities based on sensor data through the IoT framework. Statistical analysis of cloud-stored IoT data determines prediction accuracy.

Notably, the K-Nearest Neighbour algorithm outperforms traditional classifiers, establishing its effectiveness in health condition prediction.

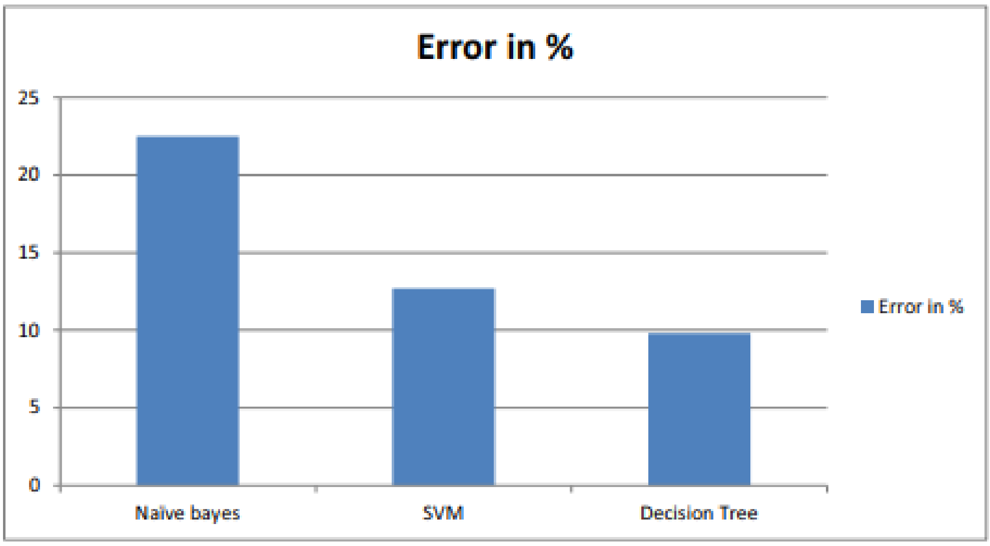

Fig. 3. Resulting error rates from categorization algorithms

Existing methods often rely on n-gram techniques and semantic models for clustering, but their efficacy can be limited. The model, developed based on Mesh ontology, addresses this by incorporating a term frequency and inverse gravity moment factor for improved class distinction. A modified n-gram technique is employed to enhance phrase identification by addressing substitution and deletion cases. The proposed approach boosts the efficiency of k-means and hierarchical clustering algorithm. Experiments conducted on PubMed documents using Mesh ontology and various measures validate the effectiveness of the approach in improving clustering accuracy.

Thouheed Ahmed et al [29]introduced a novel approach for reducing recursive image in Cloud environments. The technique employs pixel value density matching coupled with edge extraction. Evaluated on 12,800 distinct UCL ML repository samples, the proposed technique achieves a 97.8% accuracy rate. The study emphasizes evaluation and processing time as key factors. The approach is implemented and fine-tuned on the HADOOP platform to optimize big data infrastructure, showcasing its potential for efficient recursive image reduction in cloud-based settings.

Ahmed et al [30] introduced a ML algorithm aimed at regenerating signals during transfer. The process involves decomposing signals into four layers using Discrete Wavelet Transform before transfer for improved optimization. The study employs the Real-Time Signal Re-Generator and Validator Algorithm, based on neural network models. Results highlight a consistent performance score of 1.15 across 667 processed EEG samples, with an average regeneration and training processing time of 0.65 seconds. This approach showcases promising potential for enhancing signal quality during transmission through efficient regeneration and validation techniques.

Existing methods such as multiple regression and artificial neural networks (ANN) possess limitations. They demand high-quality data for accurate results and suffer from data inaccuracies or noise. Scalability is hindered by time-consuming computations for large datasets. Privacy concerns risk patient data exposure. Document modifications impact performance. Standardization, synchronization, unstructured data, and bias challenges emerge. Initial conditions' sensitivity and rendering methods influence outcomes. Addressing data quality, scalability, privacy, synchronization, unstructured data, bias, and rendering methods is imperative for the effective use of multiple regression and ANN techniques.

3. Materials And Methods

For the purpose of forecasting numerous diseases, we presented two hybrid DL models CNN-Bi-LSTM, CNN-GRU. The model's structure is as follows:

- CNN-Bi-LSTM is the first model.
- CNN-GRU is the second model.
- SVM performs the role of the meta learner in the ensemble model.

In the proposed work, the first step involved collecting datasets, which were sourced from the YBI Foundation's repository, followed by data preprocessing. Subsequently, the prediction method was executed using the preprocessed data, employing an ensemble model as the chosen approach. To assess its effectiveness, the prediction performance was analyzed and compared with existing methods, offering insights into the model's capabilities. Figure 4 illustrates the fundamental framework of the suggested system, providing a visual representation of the proposed approach.

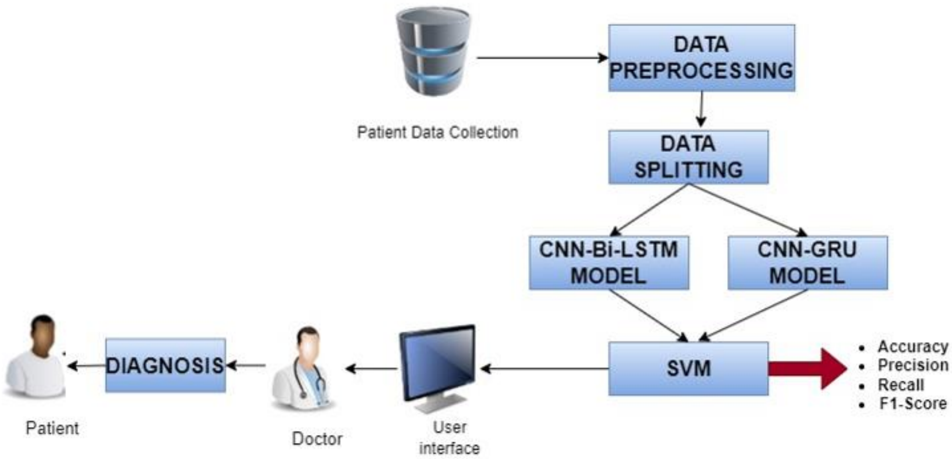

Fig. 4. Architecture of the Proposed model

3.1 Dataset Description

In a telemedicine framework, patient information can be gathered using diverse approaches to facilitate remote healthcare provision. By linking with electronic health record (EHR) systems [31], telemedicine platforms can access and retrieve pre-existing patient data from EHRs, encompassing historical medical records, test outcomes, prescription history, and other pertinent healthcare details. The data was collected from the YBI Foundation's repository. This dataset comprises 4920 rows and 133 columns. The initial 132 columns in the dataset represent distinct symptoms associated with different diseases, such as itching, skin rashes, sneezing, etc. The final column in the dataset indicates the prognosis type. The example dataset values are illustrated in figure 5 and comprise binary values of 0 and 1. A set of 41 diverse diseases are given as the reference standard or ground truth in the dataset.

	itching	skin_rash	nodal_skin_eruptions	continuous_sneezing	shivering	chills	joint_pain	stomach_pain	acidity	ulcers_on_tongue	...
0	1	1	1	0	0	0	0	0	0	0	...
1	0	1	1	0	0	0	0	0	0	0	...
2	1	0	1	0	0	0	0	0	0	0	...
3	1	1	0	0	0	0	0	0	0	0	...
4	1	1	1	0	0	0	0	0	0	0	...

5 rows × 133 columns

Fig. 5. Dataset Sample

3.2 Data Preprocessing

The descriptive statistics for each numerical column in a Data Frame are provided in the figure 6. It provides information such as the mean, standard deviation, minimum, maximum, and quartile values for each numeric feature in the dataset. This summary is helpful for gaining insights into the distribution and basic statistical properties of the data, which can be valuable for data analysis and understanding the characteristics.

	itching	skin_rash	nodal_skin_eruptions	continuous_sneezing	shivering	chills	joint_pain	stomach_pain	acidity
count	4920.000000	4920.000000	4920.000000	4920.000000	4920.000000	4920.000000	4920.000000	4920.000000	4920.000000
mean	0.137805	0.159756	0.021951	0.045122	0.021951	0.162195	0.139024	0.045122	0.045122
std	0.344730	0.366417	0.146539	0.207593	0.146539	0.368667	0.346007	0.207593	0.207593
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

8 rows × 132 columns

Fig. 6. Dataset Description

The number of missing values for each column is calculated. This is a quick way to assess the completeness of the dataset and identify columns with missing data, which is important for data preprocessing and analysis. It is possible to generate a correlation matrix for each column in a dataset, which displays pair wise correlations between numerical columns and indicates the direction and strength of their linear interactions. “A strong negative correlation is represented by a correlation value of 1, a strong positive connection is represented by a correlation value of 0, and there is no correlation at all”. This analysis is useful for understanding how different features in the dataset are related to each other and can help in identifying potential patterns or dependencies between variables. The various class labels in the dataset are shown in Table 1.

Table 1. Class Labels

1	Fungal infection	22	Allergy
2	Hepatitis C	23	hepatitis A
3	Hepatitis E	24	GERD
4	Alcoholic hepatitis	25	Chronic cholestasis
5	Tuberculosis	26	Drug Reaction
6	Common Cola	27	Peptic ulcer disease
7	Pneumonia	28	AIDS
8	Dimorphic hemmorhoids(piles)	29	Diabetes
9	Heart attack	30	Gastroenteritis
10	Varicose veins	31	Bronchial Asthma
11	Hypothyroidism	32	Hypertens ion
12	Hyperthyroidism	33	Migraine
13	Hypoglycemia	34	Cervical spondylosis
14	Ostecarthristis	35	Paralysis (brain hemorrhage)
15	Arthritis	36	Jaundice
16	(vertigo) Paroymsal Positional Vertigo	37	Malaria
17	Acne	38	Chicken pox
18	Urinary tract infection	39	Dengue
19	Psoriasis	40	Typhoid
20	Hepatitis D	41	Impetigo
21	Hepatitis B		

A hologram representation of a dataset [32]is represented in figure 7 which is an advanced visualization technique that aims to portray the complex relationships and multidimensional aspects of data.

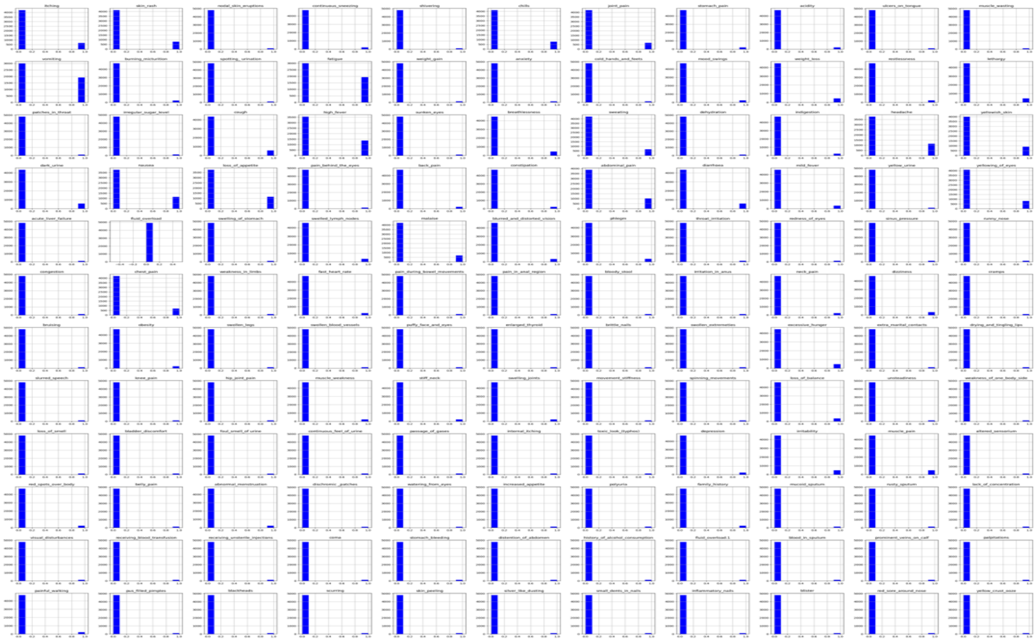

Fig. 7. Feature distribution of the data

It leverages principles from holography to create a unified and intricate visual representation by combining multiple data attributes. Unlike traditional plots, hologram representations can encompass numerous dimensions, enabling the visualization of intricate patterns, correlations, and structures that might be obscured in simpler visualizations. Through hologram representations, analysts can gain deeper insights into the underlying dynamics and complexities of their data.

A heat map visualization is a graphical representation shown in figure 8that uses color to convey the intensity of values in a two- dimensional dataset. It's often applied to matrices or tables where each cell's color indicates the magnitude of the corresponding value. Heat maps are particularly useful for identifying patterns, trends, and relationships within the data, making complex information more accessible and facilitating quick insights.

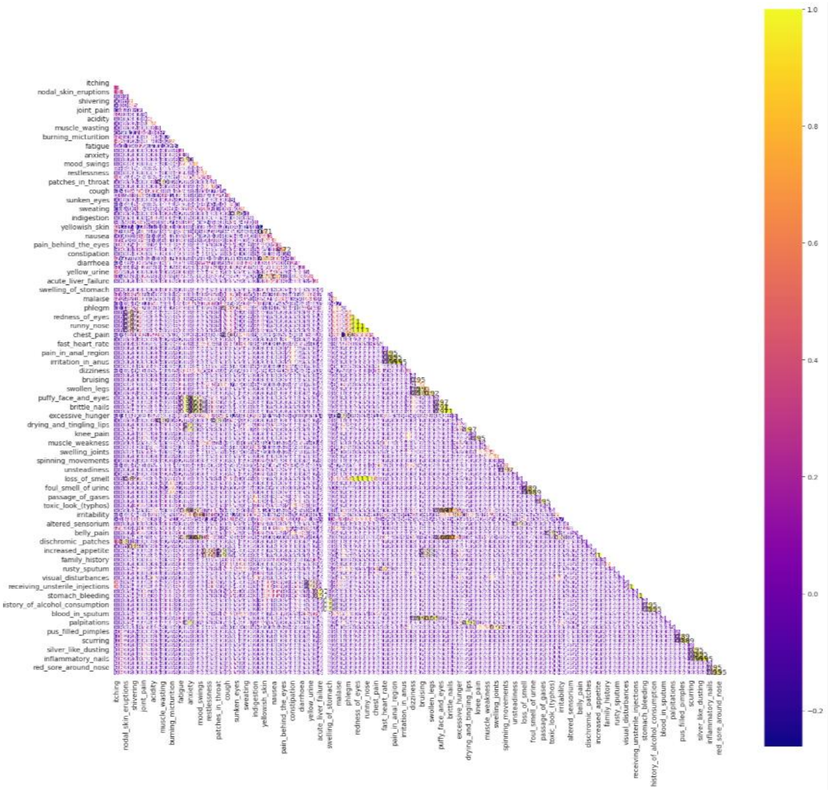

Fig. 8. Heat Map Visualization of data

3.3 CNN-Bi-LSTM Model

CNN-Bi-LSTM is a hybrid DL architecture that merges Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (Bi-LSTM) models. The CNN component specializes in capturing spatial features through convolutional layers, enabling effective feature extraction from structured data like images. On the other hand, the Bi-LSTM component excels at capturing sequential dependencies and context from data. By integrating these two architectures, CNN-Bi-LSTM leverages the strengths of both spatial and sequential analysis, making it particularly adept at tasks that involve both image-like data and sequential patterns, such as video analysis or spatiotemporal data processing.

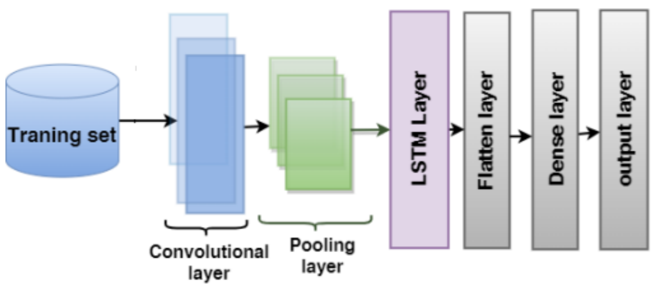

Fig. 9. CNN-Bi-LSTM model

3.4 CNN-GRU model

The CNN-GRU model is a hybrid DL architecture that combines CNN and Gated Recurrent Unit (GRU) components. CNN is utilized to capture spatial features in data through convolutional layers, making it effective for tasks like image analysis. On the other hand, GRU is a type of recurrent neural network that excels at modeling sequential dependencies in data. By fusing CNN and GRU, the CNN-GRU model leverages both spatial and sequential analysis capabilities, making it well-suited for tasks that involve data with both image-like structures and sequential patterns. This architecture is particularly valuable in scenarios such as video processing, where frames require spatial understanding, and temporal patterns necessitate sequential modeling.

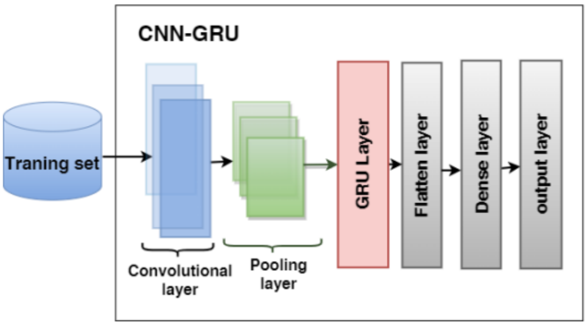

Fig.10. CNN-GRU model

3.5 Proposed Architecture

The architecture of the proposed model consists of two hybrid DL models (CNN-Bi-LSTM and CNN-GRU) and a stacking ensemble model. The architecture combines CNN and Bi-LSTM layers for sequence classification. It starts with three layers of 1D convolutional filters with increasing depths, each followed by max pooling to capture spatial features. Subsequently, Bidirectional LSTMs with 64 units are used to capture temporal dependencies bidirectional, with a dropout layer to mitigate over fitting. Two dense layers with 50 units each process features before flattening. A third dense layer with softmax activation for multi-class classification among 41 classes comes after the second dense layer with L2 regularization promotes generalization. This architecture combines spatial feature extraction from CNNs and sequential understanding of LSTMs, facilitating complex pattern recognition and classification in sequential data. Regularization and dropout aid in preventing over fitting and enhancing generalization.

The architecture of the "cnn_gru_model" integrates Convolutional Neural Network (CNN) with GRU layers to address sequence classification. The model's initiation includes three 1D convolutional layers, followed by max pooling for spatial feature extraction. Subsequently, GRU layers with 64 units are utilized to capture temporal dependencies. A dropout layer aids in preventing over fitting. Dense layers, with 50 units and "relu" activation, process features before flattening. Following this, a dense layer with L2 regularization encourages generalization, culminating in a final dense layer with softmax activation for multi-class classification within 41 categories. This design amalgamates CNNs' prowess in spatial feature extraction with GRUs' proficiency in sequence comprehension, rendering it effective for intricate patterns and sequential data tasks. The incorporation of regularization and dropout techniques bolsters the model's resilience.

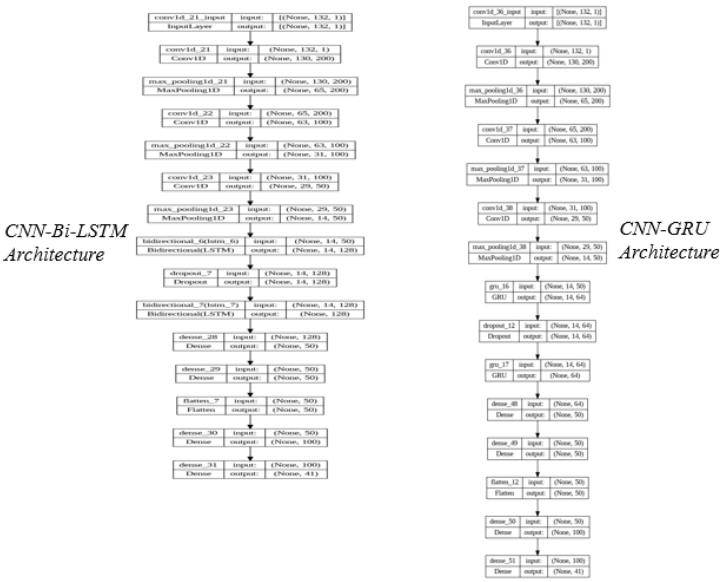

Fig. 11. Model Summary

The SVM model used here is trained on ensemble predictions and true labels to learn patterns and relationships, facilitating predictions on new instances through decision boundaries. Final predictions are leveraged by the ensemble approach, amalgamating predictions from the above models to enhance overall predictive performance.

Hyper parameters in a Convolutional Neural Network (CNN) model are critical variables that influence its architecture, training process, and overall performance. These parameters, set before training, encompass choices like loss function, optimizer, activation function, batch sizes, and number of epochs. Batch size determines the number of training examples processed in each iteration, affecting memory consumption and training efficiency. The loss function quantifies the discrepancy between predicted and actual values, guiding the optimization process. The number of epochs denotes the total iterations through the training dataset, impacting the model's convergence and potential over fitting. The thoughtful selection of these hyper parameters, often through experimentation and validation, is essential to crafting a CNN model that achieves optimal performance across various tasks and datasets.

Table 2. Hyper parameters

	CNN-Bi-LSTM	CNN-GRU
Total Parameters	251,887	138,223
Trainable Parameters	251,887	138,223
Non-Trainable Parameters	0	0
Loss	Sparse Categorical Crossentropy	
Optimizer	Adam	
Activation Function	ReLu, SoftMax	
Batch Size	32	
Number of Epochs	10	

3.6 Performance Parameters

Performance parameters serve as crucial benchmarks to evaluate its effectiveness in various tasks. These parameters encompass metrics such as precision, recall, accuracy, and F1-score, which collectively measure the model's ability to correctly classify and differentiate between different classes.

Performance Metrics	Equation
Accuracy	$\frac{(TP+FP)}{(TP+FP+TN+FN)}$
Precision	$\frac{(TP)}{(TP+FP)}$
Recall	$\frac{(TP)}{(TP+FN)}$
F1-Score	$2 \times \frac{(Precision \times Recall)}{(Precision + Recall)}$
where TP= True Positive, TN= True Negative, FP= False Positive, FN= False Negative.	

Table 3. Performance parameters

4. Result And Analysis

4.1 Hardware and Software Setup

For the sake of a dependable and stable computational setting, this study chooses Google Colaboratory [33] along with Microsoft Windows 10 as the favored platforms. Within this arrangement, the configuration comprises an Intel Core i7-6850K processor operating at 3.60 GHz with 12 cores, in addition to an NVIDIA GeForce GTX 1080 Ti GPU with 2760 memory and 4MB capacity.

4.2 Experimental Results

Table 4. Classification Report of the Model

Performance Metric	CNN-Bi-LSTM	CNN-GRU	Ensemble Model
Accuracy	0.98983	0.99119	0.9952
Precision	0.99036	0.99189	0.9954
Recall	0.99036	0.99107	0.99574
F1-Score	0.98987	0.99105	0.99541

The accuracy plot showcases how well the model's predictions match the actual labels in the training datasets as the training progresses through epochs. Increasing accuracy indicates improved learning and capability to classify data accurately. Conversely, the loss plot depicts the model's convergence over epochs by illustrating how the chosen loss function decreases as the model adjusts its parameters. Lower loss values signify better alignment between predictions and actual values.

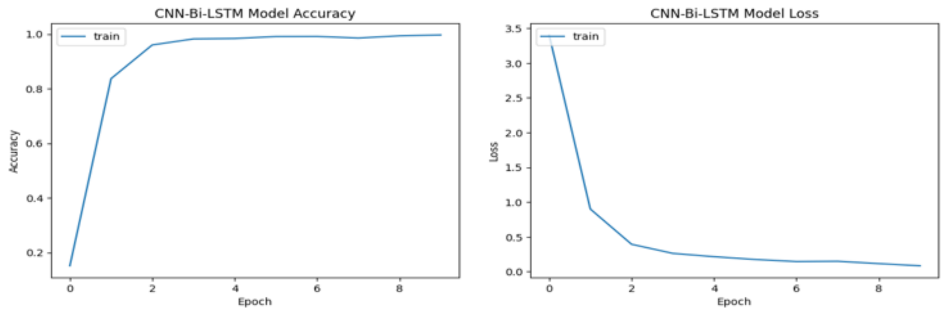

Fig. 12. Accuracy and loss plot of CNN-Bi LSTM model

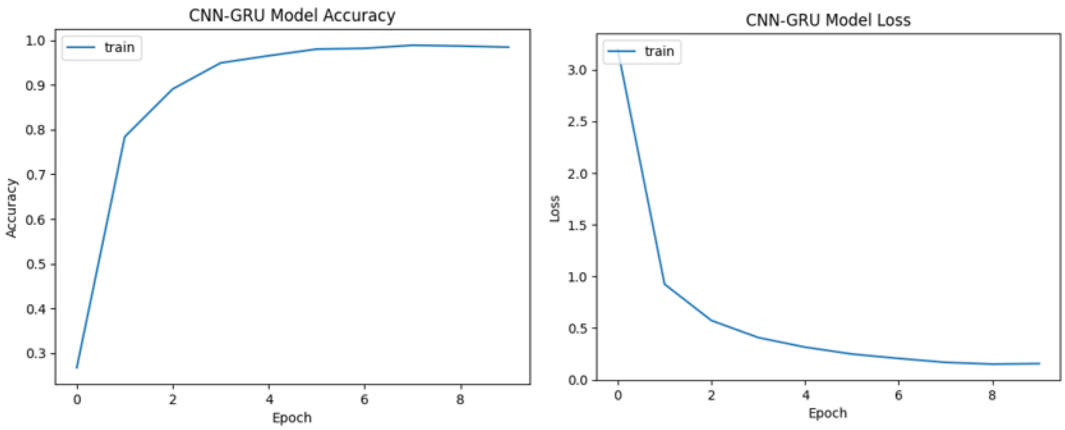

Fig. 13. Accuracy and loss plot of CNN-GRU model

The prediction results obtained are made readily available to healthcare providers, facilitating seamless access to critical diagnostic information. Through a real-time interactive system, patients and healthcare providers can engage effectively in discussions related to diagnosis and treatment planning. This system empowers patients to access high-quality healthcare services without the necessity of undertaking extensive travel, thus eliminating the time, financial, and logistical burdens typically associated with transportation.

Table 5. Obtained Output

Input Data	Predicted Disease
[1,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]	Fungal infection
[0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,1,0,0,1,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]	AIDS
[1,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,1,0,1,1,0,0,0,1,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]	Chronic cholestasis

Our novel ensemble learning based hybrid method outperforms existing techniques that rely solely on LSTM, CNN, or Bi-LSTM models. By combining the strengths of these individual methods, our approach achieves superior accuracy, precision, recall, and F1-score in comparison. While traditional methods struggle with certain complexities, our ensemble approach harnesses the complementary features of these models, resulting in a more comprehensive understanding of the data and improved performance metrics. This synergy allows us to make more accurate predictions, achieve higher precision in identifying relevant instances, capture a greater proportion of true positives through enhanced recall, and strike a better balance between precision and recall as indicated by the higher F1-score.

Table 6. Comparison of some other existing methods

Performance Parameters	LSTM Network	CNN-Bi- LSTM Network	Ensemble Model
Accuracy	98.51%	98.98%	99.52%
Precision	98.32%	99.03%	99.54%
Recall	98.05%	99.04 %	99.57%
F1-Score	98.18%	98.99%	99.541%

5. CONCLUSION

Telemedicine emerges as a vital tool in expanding healthcare accessibility, particularly in remote areas and during crises, offering unprecedented convenience. This study has demonstrated the power of data mining techniques in telemedicine, enabling the extraction of crucial insights from complex medical data, thus enhancing early disease detection and personalized care.Our approach, harnessing two hybrid DL models (CNN-Bi-LSTM, CNN-GRU) within a stacking ensemble framework with SVM as the meta-learner, has showcased its efficacy in predicting multiple diseases using telemedicine-derived features. Leveraging a dataset sourced from the YBI Foundation's repository and conducting extensive experimentation, we have achieved remarkable results, including 99.52% accuracy, 99.54% precision, 99.57% recall, and a 99.54% F1-score.We have conducted a comparative analysis of our approach with other existing methods. These exceptional outcomes underscore the potential of unified model architectures in revolutionizing disease prediction through telemedicine. Beyond the realm of predictive healthcare, our research also highlights the effectiveness of ensemble learning in handling intricate medical datasets, ultimately contributing to more informed clinical decisions and improved patient outcomes.

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