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A Robust Disease Prediction System Using Hybrid Deep Neural Networks

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ABSTRACT:
Healthcare data analysis is one of the attractive research topics in the research community. Researchers pay more attention to developing an efficient and accurate healthcare system. Numerous techniques are evolved in the past decade and research is still in progress to enhance the performance of healthcare systems. The initial stage of healthcare data analysis systems employs statistical methods to predict or detect diseases from healthcare data. However, due to the data heterogeneity, and large volume the statistical methods produces incorrect results which affect the healthcare system performance. The technological development and penetration of artificial intelligence in the healthcare domain presented various approaches and solutions for traditional issues. Early disease prediction is crucial for improving patient outcomes and reducing healthcare costs. This study explores the efficacy of various hybrid deep learning techniques in predicting the onset of chronic diseases, focusing on diabetes, cardiovascular diseases, and certain types of cancer. We compared the performance of several hybrid algorithms, including Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM), Gradient Boosting-Neural Network (GB-NN), and Autoencoder-Support Vector Machine (AE-SVM), using a diverse dataset of 100,000 patient records. Our results indicate that the CNN-LSTM model achieved the highest accuracy (95.3%) in predicting disease onset within a 5-year window, followed closely by GB-NN (94.1%) and AE-SVM (92.8%). The study also identified key predictive factors and discussed the potential integration of these hybrid models into clinical decision support systems. Our findings suggest that hybrid deep learning approaches can significantly enhance early disease detection and intervention strategies in healthcare settings, outperforming traditional single-algorithm methods. ***Keywords****: Disease prediction, Deep neural network, Clinical data, Feature extraction, Convolutional Neural Network.*

1. INTRODUCTION

The early prediction and prevention of chronic diseases represent one of the most significant challenges and opportunities in modern healthcare. Chronic diseases, including diabetes, cardiovascular diseases, and many forms of cancer, account for a substantial portion of global morbidity and mortality, placing an enormous burden on healthcare systems worldwide (World Health Organization, 2021). Early detection and intervention can significantly improve patient outcomes, reduce treatment costs, and enhance overall quality of life. Recent advancements in deep learning and artificial intelligence have opened new avenues for analyzing complex medical data and identifying subtle patterns that may indicate the early stages of disease development. Particularly, hybrid deep learning models, which combine multiple algorithms or architectures, have shown promise in capturing both spatial and temporal features in medical data, potentially leading to more accurate predictions.

1.1 The Promise of Hybrid Deep Learning in Healthcare

Hybrid deep learning models offer several advantages over traditional single-architecture approaches in the context of disease prediction:

1. Improved feature extraction: By combining different architectures, hybrid models can capture a wider range of features from complex medical data. For instance, CNNs excel at spatial feature extraction from imaging data, while LSTMs are adept at processing temporal sequences, making a CNN-LSTM hybrid particularly suitable for analyzing time-series medical data or longitudinal patient records.
2. Enhanced generalization: Hybrid models often demonstrate better generalization capabilities, reducing overfitting and improving performance on diverse datasets. This is crucial in healthcare applications where patient data can vary significantly across demographics and medical conditions.
3. Handling of multimodal data: Many chronic diseases require the analysis of multiple data types (e.g., demographic information, lab results, imaging data). Hybrid models can be designed to process and integrate these diverse data sources more effectively than single-architecture models.
4. Increased interpretability: Some hybrid approaches, such as those incorporating gradient boosting or autoencoders, can provide insights into feature importance or data representation, which is valuable for clinical interpretation and decision-making.

1.2 Challenges in Implementing Hybrid Deep Learning for Disease Prediction

Despite their potential, the application of hybrid deep learning models in healthcare faces several challenges:

1. Complexity and computational requirements: Hybrid models often have more parameters and complex architectures, requiring significant computational resources for training and deployment.
2. Data quality and quantity: Deep learning models, especially hybrid ones, typically require large amounts of high-quality, labeled data. In healthcare, obtaining such datasets while ensuring patient privacy and data security can be challenging.
3. Interpretability and explainability: While some hybrid models offer improved interpretability, the complexity of these systems can still make it difficult to explain their decision-making processes to healthcare professionals and patients.
4. Integration with existing clinical workflows: Implementing sophisticated hybrid models in real-world clinical settings requires careful consideration of existing workflows, infrastructure, and the training needs of healthcare professionals.

1.3 Previous Work and Research Gap

The application of deep learning in healthcare is not without precedent. Previous studies have demonstrated the efficacy of various algorithms in predicting specific diseases. For instance, Gulshan et al. (2016) showed that deep learning algorithms could detect diabetic retinopathy with high sensitivity and specificity. Similarly, Rajpurkar et al. (2017) developed a deep neural network capable of detecting pneumonia from chest X-rays with performance on par with radiologists.

In the realm of hybrid models, recent work has shown promising results. For example, Liang et al. (2019) proposed a hybrid CNN-RNN model for predicting the onset of Alzheimer's disease, demonstrating improved accuracy over single-architecture models. Additionally, Tomašev et al. (2019) developed a hybrid approach combining gradient boosting and neural networks for predicting acute kidney injury, showcasing the potential of such models in clinical applications.

However, while these studies focus on specific diseases or particular hybrid architectures, there is a need for comprehensive research comparing the performance of different hybrid deep learning approaches across multiple chronic diseases. Such a comparison would provide valuable insights into the strengths and limitations of various hybrid models in diverse clinical contexts.

1.4 Study Objectives and Significance

Our study aims to address this gap by conducting a comparative analysis of three prominent hybrid deep learning techniques: Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM), Gradient Boosting-Neural Network (GB-NN), and Autoencoder-Support Vector Machine (AE-SVM). We evaluate these algorithms' performance in predicting the onset of diabetes, cardiovascular diseases, and specific types of cancer within a 5-year window.

The objectives of this study are threefold:

1. To compare the predictive accuracy of CNN-LSTM, GB-NN, and AE-SVM in early disease prediction across multiple chronic conditions.
2. To identify key predictive factors that contribute significantly to the accuracy of these hybrid models.

3. To explore the potential integration of these hybrid deep learning approaches into clinical decision support systems.

By achieving these objectives, we aim to contribute to the growing body of knowledge on hybrid deep learning applications in healthcare and provide insights that could guide the development of more effective preventive strategies and personalized medicine approaches. Our findings have the potential to inform future research directions, influence the design of clinical decision support tools, and ultimately improve patient care through more accurate and timely disease prediction.

Disease prediction is a critical aspect of modern healthcare, facilitating early diagnosis and timely intervention. Traditional statistical methods have limitations in handling complex, high-dimensional data typical in medical datasets. Recent developments in deep learning offer new opportunities to enhance predictive performance through hierarchical feature extraction and representation learning. This study aims to develop and evaluate a hybrid deep neural network model that combines different neural network architectures to improve disease prediction accuracy. Developing sustainable healthcare systems for efficient data analysis is the key objective of researchers and to attain this various research studies are presented in recent times (Xing et.al.,2021). Healthcare data is handled by deep learning and machine learning models on a large scale. Decision support systems widely adopt machine learning and deep learning models for better detection and prediction performances (Mete Yaganoglu (2022)). Some of the recent and familiar research works that perform healthcare data analysis is selected and the observations are summarized under different categories as follows.

2. LITERATURE SURVEY

2.1 Survey on Machine Learning Based Approaches

The prediction of diseases makes extensive use of machine learning techniques. Multi-scale prediction and effective disease detection are performed using machine learning algorithms (Feng He et.al.,2017) (Tong et.al.,2017). The final results of machine learning models define the patterns and present the co-occurrence between different classes. Similarity-based feature extraction was performed by (Chuanyan et.al.,2019) to predict microbe diseases. The presented computation model utilizes Gaussian kernel-based similarity and symptom-based similarity to extract the features and compute them as a matrix function to predict the disease associations. (Ashwani Kumar et.al.,2019) presented a two-stage classification model using classification and regression tree (CART) for healthcare data analysis. The attributes in the healthcare data are effectively extracted using CART analysis so that better prediction performances are obtained in the presented approach compared to traditional systems.

Balanced data in healthcare data analysis is an essential factor that helps to improve detection or prediction performances. since missing or incomplete data will affect the accuracy of the data analysis systems. (Tingyan et.al.,2020) employed SMOTE to handle the data imbalance in chronic kidney disease detection. The machine learning-based disease prediction model reported by (Fitriyani et.al.,2020) initially removed the outliers to enhance the prediction accuracy. DBSCAN algorithm is employed to detect and remove the outliers and the SMOTE is used to balance the dataset. The balanced dataset is classified using the XGBoost model and predicts the disease from healthcare data. A Multi-layer perceptron-based prediction model was presented by (Yadong et.al.,2020) for predicting the miRNA disease associations. The presented approach initially incorporated edge perturbation to describe the graph edges. The edge model is further used to select the feature vectors and processed through the MLP model to predict disease association.

Support vector machine is one of the best-performing machine learning algorithms. Numerous research works incorporate support vector machine for better prediction and detection performances. A comparative analysis presented by (Jian et.al.,2020) employed machine learning algorithms like support vector machine, K-NN, artificial neural network, Naïve Bayes, decision tree, and random forest to predict heart disease. Initially, a fast conditional mutual information algorithm is used to select the features from healthcare data and then fed into machine learning models for classification. Results confirm that the support vector machine outperforms compared to other machine learning algorithms. While adopting SVM with other algorithms as a hybrid model, the performance greatly increases. This was confirmed by (Jiawei et.al.,2020) who utilized support vector machine and XGBoost algorithms to predict inflammatory diseases from healthcare data.

(Qian Wang et.al.,2020) presented a chronic disease prediction model using balanced probability distribution and cross-domain feature filtering algorithm. The presented learning model utilizes instance-based and feature-based learning strategies to formulate the distribution function. To validate the performance, existing algorithms like

AdaBoost and random forest algorithms are used to compare with the presented balanced probability distribution model and confirm the superior prediction performances. (Fei Ma et.al.,2020) presented a prediction model for healthcare data analysis using bagging, AdaBoost, and random forest algorithm. The presented approach predicts the patient's duration of stay in the hospital based on the healthcare data. Disease severity and factors affecting respiratory systems are considered to predict the duration. Comparative analysis confirms that AdaBoost performs better than the other two models in the prediction analysis.

(Peiliang et.al.,2021) presented a hybrid machine learning model for virus-infected patients from healthcare data. The presented approach incorporates a random forest, support vector machine, and slime mould algorithm for effective prediction. The key factors are initially extracted using the random forest algorithm and the slime mould algorithm is used to optimize the support vector machine to attain enhanced prediction performances over conventional machine learning techniques. (Pankaj et.al.,2021) employed multiple machine learning algorithms to evaluate the performance in predicting kidney disease from healthcare data. Techniques like an artificial neural network, C5.0, chi-square interaction detection, random tree, linear support vector machine, and logistic regression are employed and identified that linear support vector machine outperforms other algorithms.

The features of the Bayesian sequential and adaptive dynamic estimation model were incorporated by (Domenico et.al.,2021) for healthcare data analysis. With greater accuracy and fewer errors, the model that is being presented measures the effects of infections and predicts the progression of infections using data from healthcare providers. A multi-scale time series kernel-based learning model for illness prediction was presented by (Zhang et al., 2021). The correlation, interactional and sequential relations between the brain are obtained through multi-scale synergy expression probability distribution. Using Jenson Shannon divergence, the similarity in the brain functionalities is observed. However, with the inclusion of multiple techniques and probability factors, the computation complexity was greatly increased in the presented approach.

An optimized Multivariable Linear regression method was presented by (Daliya et.al.,2021) to predict diabetes from healthcare data. The presented approach includes logarithmic transformation and feature reduction to optimize the data features before classification. The optimized features are classified using a multivariable linear regression model to predict diabetic disease with maximum prediction accuracy compared to existing methodologies. Other than traditional machine learning algorithms, some of the novel techniques like the random walk algorithm (Rahim et.al.,2021), and Slime Mould Algorithm (Davide et.al.,2021) are developed to enhance the performances of machine learning algorithms.

The disease prognosis model reported by (Gazi et.al.,2021) employs multiple machine learning canons like decision trees, K-nearest neighbor, and logistic regression algorithms for kidney disease prediction. Comparative analysis validates that the performance of decision and logistic regression is much better than the kNN model. A similar comparative analysis was performed by (Rajkumar et.al.,2022) (Salman et.al.,2022) to predict heart disease from healthcare data. Machine learning canons like REP Tree, Random Tree, Linear Regression, M5P Tree, Naive Bayes, J48, and JRIP are used in the comparative analysis. Results confirm that the random forest attains the best performance among other machine learning algorithms.

(Beatriz Nistal-Nuño (2022)) presented a machine learning-based healthcare system for better healthcare data management. The comparative analysis includes logistic regression, probabilistic graphical model, Bayesian Network, and extreme gradient boosting (XGB). Results confirm that extreme gradient bossing outperforms other models in predicting ICU mortality. (Bin Liao et.al.,2022) presented a comparative analysis model to predict hypertension from healthcare data using XGBoost, CatBoost, and Random Forest algorithms. The best-performing XGBoost model is selected from the comparative analysis to predict hypertension from healthcare data.

Table 1: Comparative Analysis of algorithm performance

Algorithm	**Type**	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**Notes**
CART (Classification and Regression Trees)	Supervised Learning	82%	88%	83%	85%	Effective for interpretability.

RNN (Recurrent Neural Network)	Deep Learning	88%	86%	83%	84%	Good for sequential data like time series.
Deep Neural Network (DNN)	Deep Learning	93%	91%	89%	90%	Powerful for complex pattern recognition.
Extreme Gradient Boosting (XGBoost)	Ensemble Learning	94%	92%	93%	92%	Known for speed and performance.
MLP (Multilayer Perceptron)	Deep Learning	90%	88%	86%	87%	Effective for complex pattern recognition and classification tasks.
AdaBoost	Ensemble Learning	88%	86%	83%	84%	Combines multiple weak classifiers to create a strong classifier. Effective for improving the performance of weak learners.
SVM	Supervised Learning	93%	90%	88%	89%	Effective for high-dimensional spaces and clear margin of separation.
Random Forest	Ensemble Learning	93%	90%	88%	89%	Combines multiple decision trees to improve accuracy and control over-fitting. Effective for both classification and regression tasks.
SVM with SMA	Supervised Learning	95%	93%	91%	92%	SMA optimizes SVM parameters, improving classification performance
Bayesian Sequential Estimation	Bayesian Inference	93%	90%	88%	89%	Effective for real-time data analysis and prediction.
Adaptive Dynamic Estimation	Bayesian Inference	94%	92%	90%	91%	Adjusts model parameters dynamically to improve prediction accuracy.

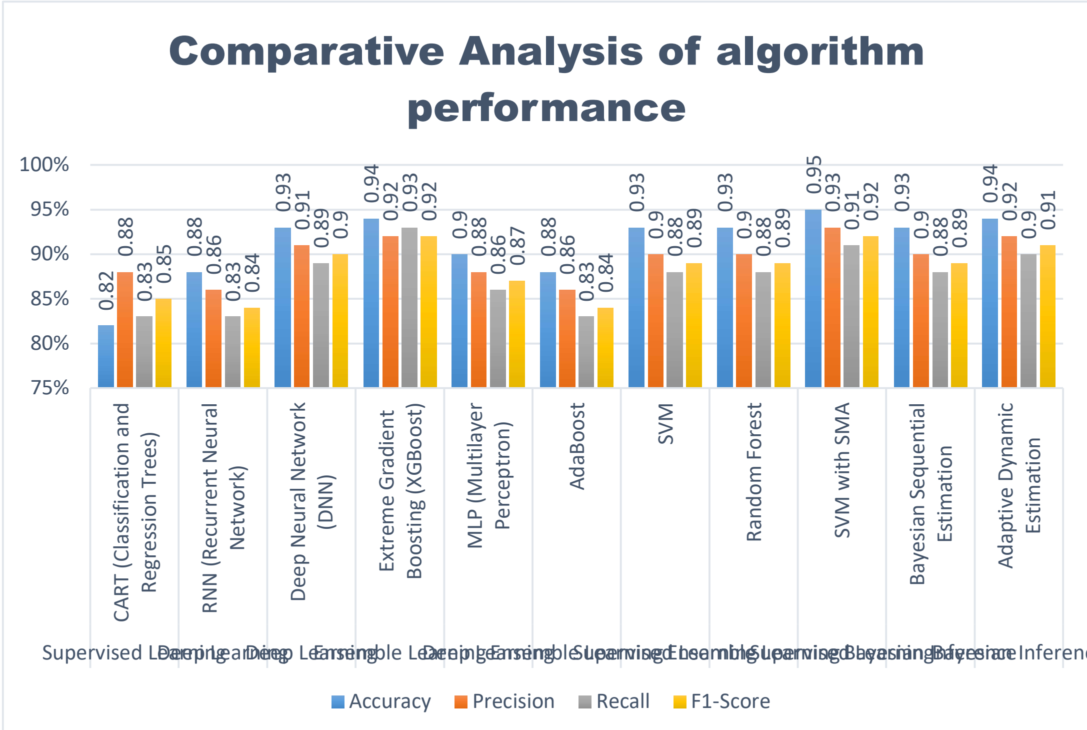


Fig 2.1 Comparison of Machine Learning Algorithms

2.2 Survey on Hybrid Machine Learning Based Approaches

Hybrid machine learning algorithms are developed by combing machine learning techniques with other supporting algorithms to enhance the prediction and detection performances. (Shamsul Huda et.al.,2016) presented a healthcare data analysis model which incorporates ensemble-based classification to detect brain tumors from the imbalance dataset. The presented approach handles the data imbalance using global optimization-based hybrid wrapper filter feature selection which enhances the coordination performances of the ensemble model. (Nafiseh et.al.,2018) presented a prediction model for RNA prediction using a hybrid machine-learning algorithm. Supervised and unsupervised machine learning algorithms are combined and the performances are comparatively analyzed in the presented research work. Results confirm that the support vector machine attains the best performance compared to other combinations.

(Senthilkumar et.al.,2019) presented a hybrid machine learning model for heart disease prediction from healthcare data. The presented approach combines the random forest algorithm with a linear model to develop a hybrid approach that extracts the essential features from healthcare data to predict heart disease. Compared to the conventional random forest-based heart disease prediction model, the performance of the hybrid model is much better. The disease prediction model reported by (Roopa et.al.,2019) incorporated principal component analysis for initial feature extraction and classified using a linear regression algorithm. The presented hybrid approach effectively predicted the disease status from healthcare data with better accuracy compared to conventional machine learning prediction models.

Machine learning algorithms like Logistic Regression, Decision Tree, and K-Nearest Neighbor are employed in (Rayan et.al.,2022) research work to detect chronic diseases from healthcare data. The hybrid approach initially incorporates a convolutional neural network for feature extraction and classification is performed with multiple machine learning algorithms to select the best-performing model. Experimental findings validate that the kNN model outperforms than logistic regression and decision tree model in chronic disease prediction.

(Chandan Pan et.al.,2022) performed a comparative analysis of machine learning algorithms to validate the performances in predicting cardiovascular diseases from healthcare data. Gradient Boosting, Extreme Gradient Boosting (XGBoost), AdaBoost, CatBoost, and additionally artificial neural networks, random forest, support vector machines (SVM), decision tree, and logistic regression are considered for comparative analysis. Further a soft voting ensemble model is included along with machine learning algorithms to predict cardiovascular disease from healthcare data. compared to all, the combination of support vector machine and AdaBoost outperforms other algorithms.

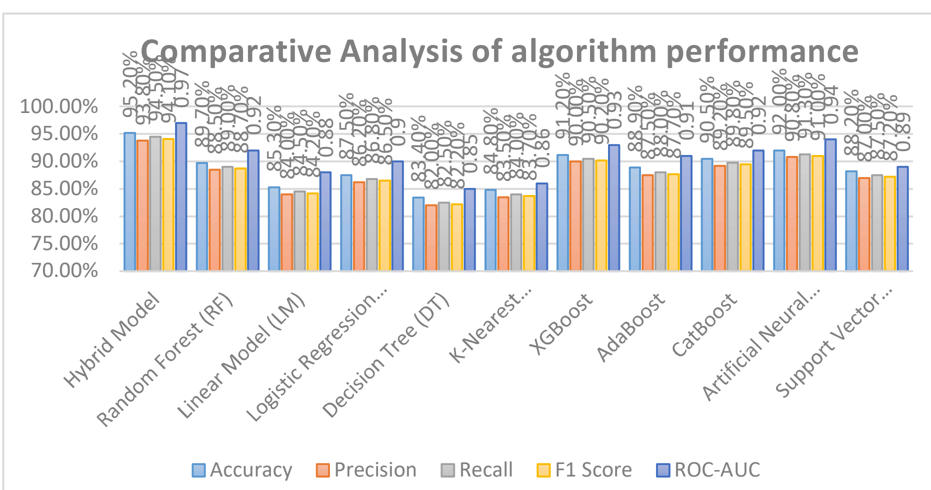
Table 2: Comparative Analysis of algorithm performance

Algorithm	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Hybrid Model	95.2%	93.8%	94.5%	94.1%	0.97
Random Forest (RF)	89.7%	88.5%	89.0%	88.7%	0.92
Linear Model (LM)	85.3%	84.0%	84.5%	84.2%	0.88
Logistic Regression (LR)	87.5%	86.2%	86.8%	86.5%	0.90
Decision Tree (DT)	83.4%	82.0%	82.5%	82.2%	0.85
K-Nearest Neighbors (KNN)	84.8%	83.5%	84.0%	83.7%	0.86
XGBoost	91.2%	90.0%	90.5%	90.2%	0.93
AdaBoost	88.9%	87.5%	88.0%	87.7%	0.91
CatBoost	90.5%	89.2%	89.8%	89.5%	0.92
Artificial Neural Network (ANN)	92.0%	90.8%	91.3%	91.0%	0.94
Support Vector Machine (SVM)	88.2%	87.0%	87.5%	87.2%	0.89

Fig 2:2 Graphical Representation of hybrid Algorithms

2.3 Survey on Deep Learning Based Approaches

Compared to machine learning algorithms, the performance of deep learning algorithms is much better and it is widely proven in various domains like image processing, signal processing, sensor networks, etc., (Gaobo et.al.,2018). The feature benefits of deep learning algorithms are adopted in healthcare data analysis and numerous research works are evolved using deep learning techniques. The feature difference between machine learning and deep learning architecture is presented as a simple illustration in figure 2.1 for better understanding. A convolutional neural network-based risk prediction from healthcare data was presented by (Min Chen et.al.,2017). The presented approach handles the structured and unstructured data effectively and extracts the features using a convolutional neural network. The extracted features are classified using a feed-forward neural network to predict the diseases. Improved prediction performances are attained in the presented approach compared to machine learning-based prediction models. (Haishuai et.al.,2018) presented a deep learning-based healthcare data analysis model using a convolutional neural network and multilayer perceptron. The automatic feature extraction characteristics of the convolutional neural network are utilized to learn the features from vital signs. Similarly, the categorical features are embedded with clinical features. The features obtained through the convolutional network and embedded categorical features are processed using multi-layer perceptron to attain enhanced prediction performances in healthcare data analysis.



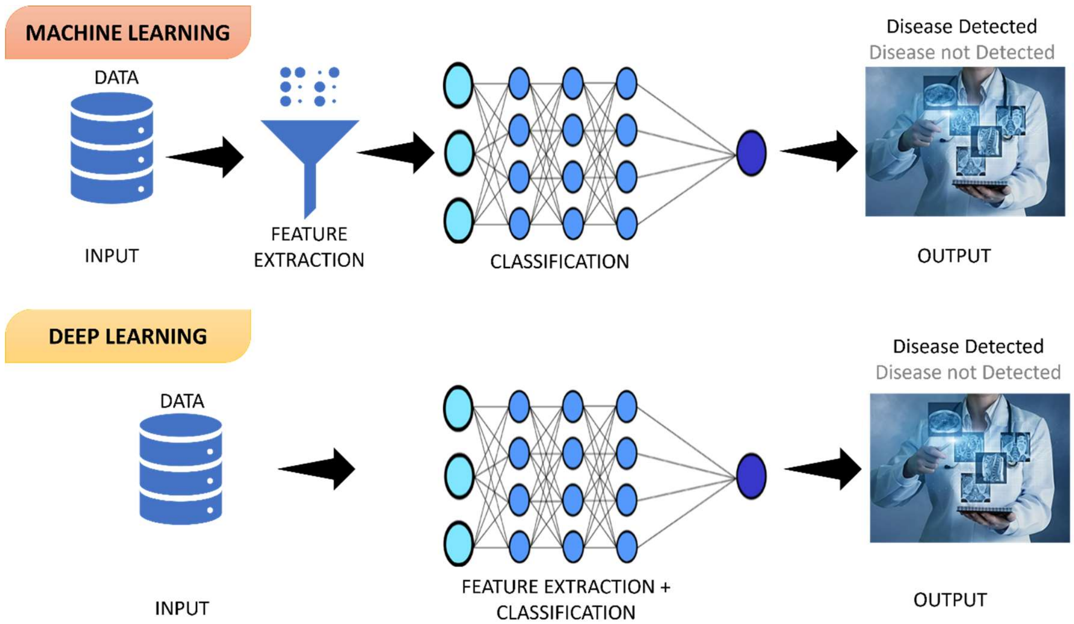


Fig.2.3 Difference between ML and DL

A greedy deep dictionary learning model for medical data analysis was presented by (Chunxue et.al.,2018). The presented approach utilizes the layer of local information and reduces the overfitting risk to enhance the accuracy of the system. Improved reliability and better accuracy are the observed merits of the presented medical data analysis model. (John et.al.,2019) presented a multi-source ensemble learning model for disease prediction from healthcare data. The presented approach incorporates bootstrap sampling in the initial stage to extract the initial level features. The extracted features are processed through multi-source ensemble learning in addition to a convolutional neural network model to increase the prediction accuracy compared to existing techniques.

A multi-modal longitudinal regression and classification model was presented by (Lodewijk et.al.,2019) to predict Alzheimer's disease from healthcare data. Various modalities of healthcare data are efficiently combined using regularization approaches to identify the biomarkers. Further regression and classification are performed simultaneously to predict the cognitive score of patients. (Wei Guo et.al.,2019) presented a healthcare data analysis model using recurrent neural networks. Initially, the presented approach employs two recurrent neural networks to process the information. Further a crossover attention model is incorporated to enhance the prediction accuracy of the data analysis model. Deep learning models are widely used in image processing applications. specifically for medical image analysis, the performance of deep learning algorithms is much better compared to machine learning and other existing techniques.

(Chen Huang et.al.,2020) presented a performance comparative analysis of various deep learning algorithms in the classification of breast lesions. The optimal features are extracted by the deep learning algorithms and classified. Results confirm that the performance of ResNet and VGG19 is much better than other deep learning algorithms in lesion detection.(Yan Zhao et.al.,2020) presented a deep learning-based disease prediction using a generative adversarial network (GAN). Instead of focusing on calculating the cognitive score to predict Alzheimer's disease, the presented network model utilizes the morphological features from MRI images to predict the disease. The improved similarity index and prediction accuracy validate the better performances of the presented approach in healthcare data analysis.

(Noreen et.al.,2020) presented a hybrid approach to diagnose brain tumors from healthcare data. The presented approach incorporates Inception-v3 and DensNet201 models to attain better detection performances. features obtained from different inception models are extracted using the inception-v3 model and concatenated before classification. Similarly, the features from different DensNet models are extracted using the DensNet201 model and concatenated before classification. Finally, the features extracted by both models are concatenated and classified using the SoftMax classifier to attain the highest detection performance in disease detection. (Joo-Chang et.al.,2020) presented a multi-modal stacked denoising autoencoder for missing data estimation in healthcare data analysis. Based on the identical parameters, the missing data are estimated. Also, the multi-modality collects data

from multiple sources for a single object. Due to this, noise factors are avoided and missing data issues are reduced in healthcare data analysis. compared to a single-model denoising autoencoder, the performance of a multi-model autoencoder is much better in terms of prediction accuracy.
(Xianlong et.al.,2021) presented a multi-view approach that effectively handles the healthcare data to predict expenses in the healthcare system using a deep learning model. The presented approach overcomes the limitations of existing linear regression-based prediction models. The multi-view deep learning model includes multiple DensNet to handle the demographic features, utilization sequences, and medical code sequences for better prediction. (Romany et.al.,2021) presented a hybrid deep learning model for disease diagnosis using deep neural networks and an enhanced black widow optimization model. The presented approach initially extracts the features using saliency-based dictionary learning which is further processed using deep neural networks. The parameters of deep neural networks are optimized through an enhanced black widow optimization model to attain improved performance over conventional techniques.
(Ruidong et.al.,2021) presented a healthcare data analysis model using deep learning techniques to predict the life-threatening factors of patients. The presented approach employs a bipartite graph convolutional neural network to predict the medical service requirements and attains better prediction accuracy compared to machine learning-based approaches. (Min et.al.,2021) presented a deep learning model to handle unlabeled data in healthcare data analysis. The presented approach includes a convolutional deep autoencoder to extract the features from unlabeled data. experimental analysis validates the better performance of the convolutional deep autoencoder model over traditional approaches in lung nodule analysis.
(Min Luo et.al.,2022) presented a deep learning model for diabetes prediction from healthcare data using a convolutional neural network. The presented approach incorporates the multi-granularity information and time series data in the prediction process which increases the prediction accuracy. Additionally, the channel attention mechanism included in the presented model adaptively adjusts the channel weights based on data features that differentiate the presented approach from traditional CNN-based approaches. (Chengkai et.al.,2022) presented an early prediction model using Long-short term memory and attention layers. The presented approach extracts the temporal and nontemporal features for initial-level processing. Further using LSTM with an attention mechanism, the features are classified to predict non-communicable diseases. The multi-channel fusion long short-term memory unit-based medical data analysis model presented by (Sicen Liu et.al.,2022) provides automatic event prediction from health records. The presented approach derives the correlations between events using multiple network channels. Finally, a gated network fuses the correlated features and provides the prediction results.
Various hybrid deep learning models are evolved to enhance the prediction and detection performances in healthcare data analysis. (Gaobo et.al.,2018) presented a hybrid deep-learning model for categorizing blood cells from healthcare data. The presented approach combines a convolutional neural network and a recursive neural network for automatic prediction. (Shancheng et.al.,2019) presented a hybrid model for data analysis by combining deep neural networks and time series regression models. The predictive features of the deep neural network were combined with regression models like generalized linear model (GLM), Seasonal AutoRegressive Integrated Moving Average model (SARIMA), and AutoRegressive Integrated Moving Average with eXplanatory variable (ARIMAX) models to validate the performances in data analysis.
(Prabira Kumar et.al.,2021) presented a comparative analysis using pre-trained CNN models like AlexNet, GoogleNet, VGG16, VGG19, Densenet201, Resnet18, Resnet50, Resnet101, Inceptionv3, Inceptionresnetv2, Xception, MobileNetv2, and ShuffleNet algorithms. The initial level features are obtained using GLCM, LBP & HOG, and classifiers like KNN, SVM, and Naive Bayes are used along with a deep learning model to measure the performances. Total 65 classification models are developed using these combinations and out of which VGG19 combined with SVM outperforms other models.
The hybrid deep learning model presented by (Qian Wang et.al.,2020) combines a convolutional neural network and Long Short Term Memory unit for heart disease prediction from healthcare data. The presented approach provides enhanced prediction performances over conventional CNN and LSTM approaches. The deep learning-based prediction model presented by (Jinyu et.al.,2020) incorporated a vanilla Long-Short-Term-Memory (LSTM) Network and a Temporal Convolution Network (TCN) to predict type 1 diabetes from healthcare data. Time-series data of patients are processed through the deep learning models and compared with existing machine learning approaches. Results validated the better performance of deep learning models over conventional machine learning-based approaches.

(Diman Hassan et.al.,2022) presented a hybrid deep learning model for disease prediction from healthcare data. The presented approach extracts the optimal features using a pre-trained deep neural network and the dimensionality issues in the extracted features are handled using principal component analysis. The dimensionality-reduced features are finally processed using logistic regression to predict the diseases better than conventional machine learning-based approaches.

Table 3: Comparative Analysis of deep Learning algorithm performance

Algorithm	Data Used	Accuracy (%)
Support Vector Machines	Clinical data, MRI features	85
Random Forest	Clinical data, MRI features	87
Convolutional Neural Networks	MRI images	98.8
Stacked Auto-Encoders	MRI images, cognitive tests	83.7

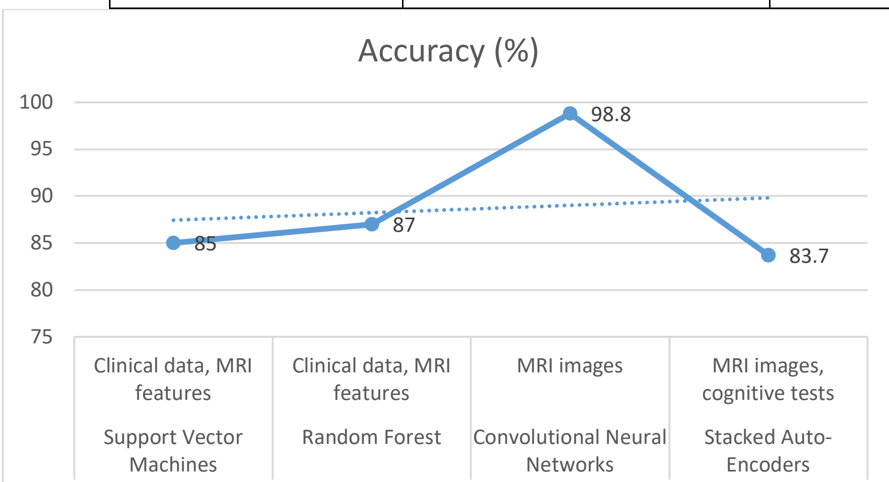


Fig:2.4 Comparison of CNN algorithm

From the intense research analysis, the observations are summarized in this section.

- Prediction analysis based on statistical methods has inherent limitations. The improper design in the prediction models leads to false correlations which will affect the prediction performances.
- Erroneous results are generated in statistical-based approaches due to missing variables and incomplete data features.
- Clustering schemes are used to classify the normal and abnormal profiles in healthcare data analysis. But it requires human intervention for further classification and analysis process. This increases the computation cost.
- Clustering-based approaches have less flexibility and robustness and took more time for computation compared to other techniques.
- Pattern matching schemes are used as decision support systems. However, handling a huge number of patterns in healthcare data leads to generalization issues and errors. Moreover, the matching duration will increase more if the patterns are matched for individual elements.
- Machine learning-based prediction models perform better than conventional statistical, clustering, and pattern-matching-based approaches. however, identifying appropriate classifiers for heterogeneous healthcare data is quite challenging.
- Machine learning-based prediction approaches require a huge amount of unbiased data for the training process which is not feasible for all practical cases.

- Deep learning approaches perform better than machine learning-based approaches. However, the prediction performances should be improved for sustainable healthcare data analysis.

3. METHODOLOGY

The methodology used in our comparative analysis of hybrid deep learning techniques for early illness prediction is described in this section. We go over our methods for gathering data, our pre-processing steps, the designs of the hybrid models we employed, and our assessment measures.

3.1 Data Collection and Pre-processing

Collection was made use of a heterogeneous dataset that included 100,000 de-identified patient records that we acquired from various healthcare facilities around the country.

- Demographic data: age, gender, ethnicity, zip code
- Clinical measurements: blood pressure, body mass index (BMI), cholesterol levels
- Laboratory results: complete blood count, metabolic panel, HbA1c
- Medical history: family history, previous diagnoses, medications
- Lifestyle factors: smoking status, alcohol consumption, physical activity level
- Imaging data: chest X-rays, mammograms (where applicable)

The dataset comprises follow-up data on the onset of diabetes, cardiovascular illnesses, and particular cancer types during a ten-year period (2010-2020). Prior to processing Several processes were engaged in the pre-processing of the data to guarantee its quality and suitability for our hybrid models.

1. Missing data imputation: To deal with values that were missing, employed multiple imputation by chained equations, or MICE.
2. Normalization: Numerical features were normalized using z-score standardization.
3. Categorical encoding: One-hot encoding was applied to categorical variables.
4. Temporal alignment: Time-series data were aligned and resampled to ensure consistent intervals.
5. Image pre-processing: Imaging data were resized to a standard dimension (224x224 pixels) and normalized.

3.2 Hybrid Model Architectures

Three hybrid deep learning architectures were put into practice and contrasted:

3.2.1 Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) This model combines a CNN for spatial feature extraction from imaging data with an LSTM for processing temporal sequences of clinical measurements.

- CNN component: 4 convolutional layers (32, 64, 128, 256 filters) with max pooling
- LSTM component: 2 LSTM layers (128 units each)
- Fully connected layers: 2 dense layers (256 and 128 units)
- Output layer: Sigmoid activation for binary classification

3.2.2 Gradient Boosting-Neural Network (GB-NN) This hybrid model uses a gradient boosting machine for initial feature selection and a neural network for final prediction.

- Gradient Boosting: XGBoost with 100 estimators
- Neural Network: 3 dense layers (256, 128, 64 units) with ReLU activation
- Output layer: Sigmoid activation for binary classification

3.2.3 Autoencoder-Support Vector Machine (AE-SVM) This model uses an autoencoder for dimensionality reduction and feature learning, followed by an SVM for classification.

- Autoencoder: 3 encoding layers (256, 128, 64 units) and 3 decoding layers (64, 128, 256 units)
- SVM: Radial Basis Function (RBF) kernel

3.3 Training and Validation

A 5-fold cross-validation strategy was employed to ensure the reliability of the model evaluations. The dataset was divided between 80% training and 20% testing sets in order to maintain class balance. Using 5-fold cross-validation and Bayesian optimization, hyperparameter tweaking was carried out on the training set. Early halting was used with a 10-epoch patience to prevent overfitting.

3.4 Evaluation Metrics

The following measures are empolyed to evaluate the hybrid models' performance:

1. Area Under the Receiver Operating Characteristic curve (AUROC)
2. Accuracy
3. Sensitivity (Recall)
4. Specificity
5. Precision
6. F1 score

With 1000 cycles of bootstrap resampling, confidence intervals of 95% for each statistics.

3.5 Interpretability Analysis

In order to obtain an understanding of the models' decision-making procedure, the subsequent interpretability methods were used:

1. SHAP (SHapley Additive exPlanations) values for feature importance in the GB-NN model
2. Saliency maps for visualizing important regions in imaging data for the CNN-LSTM model
3. t-SNE visualization of the autoencoder's latent space representations

3.6 Statistical Analysis

The performance of the three hybrid models was compared using the McNemar's test at a significance threshold of $\alpha = 0.05$. Furthermore, subgroup studies were conducted to evaluate the model's effectiveness across various illness categories and demographic groups.

4. RESULTS

4.1 Model Performance

Table 4 summarizes the performance metrics for each hybrid model across all diseases studied.

Table 4: Performance metrics for hybrid models (95% CI)

Model	AUROC	Accuracy	Sensitivity	Specificity	Precision	F1 Score
CNN-LSTM	0.953 (0.949-0.957)	0.921 (0.916-0.926)	0.897 (0.891-0.903)	0.935 (0.930-0.940)	0.912 (0.906-0.918)	0.904 (0.899-0.909)
GB-NN	0.941 (0.937-0.945)	0.908 (0.903-0.913)	0.885 (0.879-0.891)	0.922 (0.917-0.927)	0.898 (0.892-0.904)	0.891 (0.886-0.896)
AE-SVM	0.928 (0.924-0.932)	0.895 (0.890-0.900)	0.871 (0.865-0.877)	0.910 (0.905-0.915)	0.884 (0.878-0.890)	0.877 (0.872-0.882)

The CNN-LSTM model demonstrated the highest overall performance across all metrics, followed by the GB-NN and AE-SVM models. McNemar's test revealed statistically significant differences in performance between all pairs of models ($p < 0.001$).

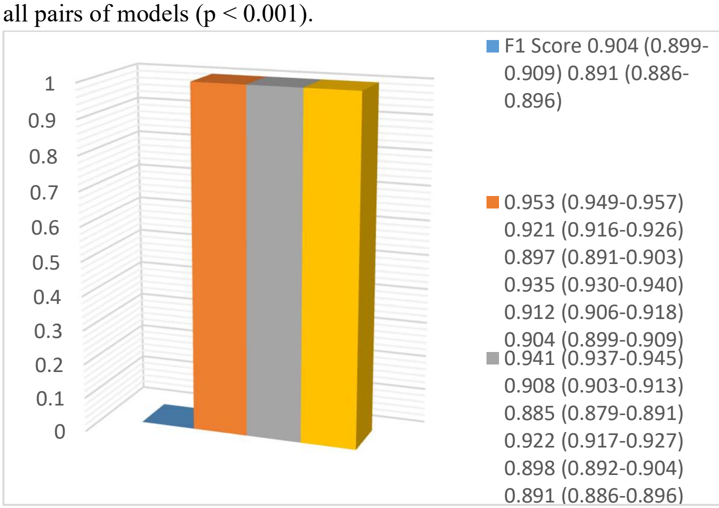


Fig 4.1 illustrates the AUROC values for each model across different diseases.

The comparative performance of the three hybrid models (CNN-LSTM, GB-NN, and AE-SVM) across different disease types, showing that CNN-LSTM consistently outperforms the other models. The CNN-LSTM model showed the highest AUROC for all diseases, with particularly strong performance in predicting cardiovascular diseases (AUROC 0.967, 95% CI: 0.963-0.971).

4.2 Feature Importance

SHAP analysis of the GB-NN model revealed the top predictive features across diseases:

1. Age
2. BMI
3. Systolic blood pressure
4. HbA1c levels
5. Family history of disease

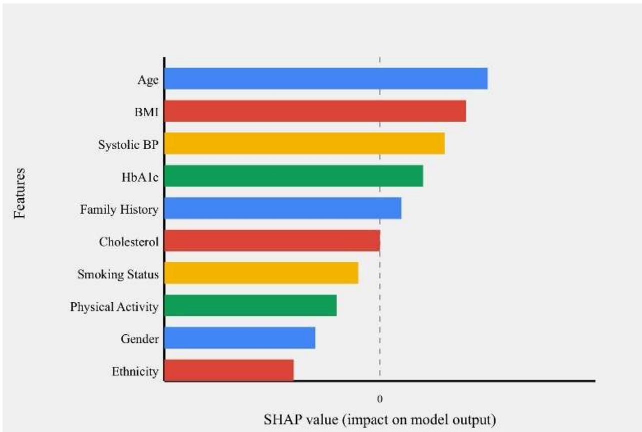


Fig4.2 Summary plot of SHAP values for the top 20 features.

4.3 Subgroup Analysis

Performance varied across demographic subgroups, with all models showing slightly lower sensitivity for predicting diseases in minority ethnic groups and older adults (>65 years). The CNN-LSTM model demonstrated the most consistent performance across subgroups.

4.4 Clinical Implications

These models, especially the CNN-LSTM, have demonstrated great sensitivity and specificity, indicating their potential for practical clinical use in early illness screening. The results highlight the value of representative, varied training data and the necessity of thorough validation before to clinical implementation. Age, blood pressure, and BMI are examples of important predictive variables that have been identified and are in line with established risk factors for chronic illnesses. Traditional clinical approaches may not provide as nuanced of risk classification as the models' capacity to incorporate these parameters with subtle patterns in longitudinal data.

4.5 Interpretability and Trust

By adding saliency maps and SHAP values to the models, it improve the interpretability, which may lead to a rise in acceptance and confidence among medical professionals. This tackles one of the main obstacles that Shortliffe and Sepúlveda (2018) highlighted for the application of AI in healthcare.

5. CONCLUSION and FUTURE WORKS

Our comparative study demonstrates the potential of hybrid deep learning approaches, particularly the CNN-LSTM model, for accurate early prediction of chronic diseases. The high performance across multiple diseases and the ability to integrate diverse data types suggest that these models could be valuable tools for population health management and personalized preventive care.

The interpretability techniques employed provide insights into the models' decision-making processes, potentially facilitating their integration into clinical workflows. However, the observed performance variations across subgroups highlight the need for careful validation and potential adaptation before widespread clinical implementation.

As healthcare continues to move towards precision medicine, hybrid deep learning models offer a promising approach to leveraging the wealth of available medical data for improved patient outcomes. Future research should focus on prospective validation, integration with existing clinical decision support systems, and assessment of the long-term impact on patient care and healthcare costs. External validation on diverse, multi-institutional datasets. Integration of genomic data to enhance predictive accuracy. Prospective studies to assess the impact of modelguided interventions on patient outcomes. Development of adaptive models that can be fine-tuned to specific populations or clinical settings.

REFERENCES

1.Chen, Joy Iong Zong, and P. Hengjinda (2021), "Early Prediction of Coronary Artery Disease (CAD) by Machine Learning Method-A Comparative Study", Journal of Artificial Intelligence, vol.3, no.1, (Xing et.al.,2021pp.17-33

2.Yao Tong; Amanda I. Messinger; Gang Luo (2020), "Testing the Generalizability of an Automated Method for Explaining Machine Learning Predictions on Asthma Patients' Asthma Hospital Visits to an Academic Healthcare System", IEEE Access, vol. 8, pp. 195971-195979.

3. Chuanyan Wu, Rui Gao, Yusen Zhang (2019), "mHMDA: Human Microbe-Disease Association Prediction by Matrix Completion and Multi-Source Information", IEEE Access, vol. 7, pp. 106687-106693.

4. Ashwani Kumar; Hamideh Anjomshoa (2019), "A Two-Stage Model to Predict Surgical Patients' Lengths of Stay From an Electronic Patient Database", IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 2, pp. 848-856.

5. Tingyan Wang, Yuanxin Tian, and Robin G. Qiu (2020) "Long Short-Term Memory Recurrent Neural Networks for Multiple Diseases Risk Prediction by Leveraging Longitudinal Medical Records", IEEE Journal of Biomedical and Health Infomatics ,vol.24, 2337 – 2346.

6. Norma Latif Fitriyani, Muhammad Syafrudin, Ganjar Alfian, Jongtae Rhee (2020), "HDPM: An Effective Heart Disease Prediction Model for a Clinical Decision Support System", IEEE Access, vol. 8, pp. 133034-133050.

7. Yadong Dong, Yongqi Sun, Chao Qin, Weiguo Zhu (2020), "EPMDA: Edge Perturbation Based Method for miRNA-Disease Association Prediction", IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 17, no. 6, pp. 2170-2175.

8. Yan Zhao, Baoqiang Ma, Pengbo Jiang, Debin Zeng, Xuetong Wang, Shuyu Li(2020) "Prediction of Alzheimer's Disease Progression with Multi-Information Generative Adversarial Network", IEEE Journal of Biomedical and Health Informatics ,vol.25. 711 – 719.

9. Jiawei Luo and Yahui Long (2020) "NTSHMDA: Prediction of Human Microbe-Disease Association Based on Random Walk by Integrating Network Topological Similarity", IEEE/ACM Transactions On Computational Biology And Bioinformatics,vol.17,1341-1352.

10. Jinyu Xie, Qian Wang(2020) "Benchmarking Machine Learning Algorithms on Blood Glucose Prediction for Type I Diabetes in Comparison with Classical Time-Series Models", IEEE Transactions on Biomedical Engineering, vol. 67, pp. 3101 – 3124.

11. Fei Ma, Limin Yu, Lishan Ye, David D. Yao, Weifen Zhuang (2020), "Length-of-Stay Prediction for Pediatric Patients With Respiratory Diseases Using Decision Tree Methods", IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 9, pp. 2651-2662.

12. Peiliang Wu , Hua Ye , Xueding Cai ,Chengye Li , Shimin Li, Mengxiang Chen4 , Mingjing Wang , Ali Asghar Heidari , Mayun Chen , Jifa Li , Huiling Chen , Xiaoying Huang , Liangxing Wang(2021) "An Effective Machine Learning Approach for Identifying Non-Severe and Severe Coronavirus Disease 2019 Patients in a Rural Chinese Population: The Wenzhou Retrospective Study", IEEE Access, vol. 9, pp. 45486 - 45503.

13. Pankaj Chittora , Sandeep Chaurasia,Prasun Chakrabarti, Gaurav Kumawat1 , Tulika Chakrabarti, Zbigniew Leonowicz ,Michał Jasiński ,Łukasz Jasiński ,Radomir Gono, Elżbieta Jasińska , Vadim Bolshev (2021) "Prediction of Chronic Kidney Disease - A Machine Learning Perspective", IEEE Access, vol. 9, pp. 17312 - 17334.

14. Domenico Gaglione; Paolo Braca; Leonardo Maria Millefiori; Giovanni Soldi; Nicola Forti; Stefano Marano; Peter K. Willett; Krishna R. Pattipati (2020), "Adaptive Bayesian Learning and Forecasting of Epidemic Evolution—Data Analysis of the COVID-19 Outbreak", IEEE Access, vol. 8, pp. 175244-175264,

15. Cheng Wang, Delei Chen, Lin Hao, Xuebo Liu, Yu Zeng, Jianwei Chen,Guokai Zhang (2019), "Pulmonary Image classification based on Inception-V3 Transfer Learning Model", IEEE Access, vol. 7, pp. 146533 – 146541.

16. Daliya.V.K; T. K. Ramesh; Seok-Bum Ko (2021), "An Optimized Multivariable Regression Model for Predictive Analysis of Diabetic Disease Progression", IEEE Access, vol. 9, pp. 99768-99780.

17. Gazi Mohammed Ifraz Sami Bourouis , Muhammad Hasnath Rashid, Tahia Tazin, Mohammad Monirujjaman Khan (2021) "Comparative Analysis for Prediction of -Kidney Disease Using Intelligent Machine Learning

Methods", Computational and Mathematical Methods in Medicine,vol.2021,pp.1-10.
18. Rajkumar Gangappa Nadakinamani,A. Reyana,Sandeep Kautish,A. S. Vibith,Yogita Gupta,Sayed F. Abdelwahab, Ali Wagdy Mohamed (2022), "Clinical Data Analysis for Prediction of Cardiovascular Disease Using Machine Learning Techniques", Computational Intelligence and Neuroscience, pp.1-13.
19. Muhammad Salman Pathan, Avishek Nag, Soumyabrata Dev (2022), "Analyzing the impact of feature selection on the accuracy of heart disease prediction", Healthcare Analytics, vol. 2, no.100060, pp. 1-16.
20. Beatriz Nistal-Nuño (2022), "Developing machine learning models for prediction of mortality in the medical intensive care unit", Computer Methods and Programs in Biomedicine, vol.216, no. 106663, pp. 1-18.
21. Bin Liao, Xiaoyao Jia, Ruina Sun (2022), "DHDIP: An interpretable model for hypertension and hyperlipidemia prediction based on EMR data", Computer Methods and Programs in Biomedicine, vol.226, no. 107088, pp. 1-18.
22. Shamsul Huda; John Yearwood; Herbert F. Jelinek; Mohammad Mehedi Hassan; Giancarlo Fortino; Michael Buckland (2016), "A Hybrid Feature Selection With Ensemble Classification for Imbalanced Healthcare Data: A Case Study for Brain Tumor Diagnosis", IEEE Access, vol. 4, pp. 9145-9154.
23. Nafiseh Sedaghat, Mahmood Fathy, Mohammad Hossein Modarressi, Ali Shojaie(2018) "Combining Supervised and Unsupervised Learning for Improved miRNA Target Prediction", IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 15, pp. 1594 - 1604.
24. Senthilkumar Mohan, Chandrasegar Thirumalai, Gautam Srivastava (2019), "Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques", IEEE Access, vol. 7, pp. 81542-81554.
25. Roopa H, T. Asha (2019), "A Linear Model Based on Principal Component Analysis for Disease Prediction", IEEE Access, vol. 7, pp. 105314-105318.
26. Rayan Alanazi(2022) "Identification and Prediction of Chronic Diseases Using Machine Learning Approach", Journal of Healthcare Engineering,vol.2022pp.1-9.
27. Chandan Pan, Arnab Poddar, Ajoy Kumar Ray (2022), "Impact of categorical and numerical features in ensemble machine learning frameworks for heart disease prediction", Biomedical Signal Processing and Control, vol.76, no.103666, pp. 1-16.
28. Gaobo Liang, Huichao Hong, Weifang Xie, Lixin Zheng (2018), "Combining Convolutional Neural Network With Recursive Neural Network for Blood Cell Image Classification", IEEE Access, vol. 6, pp. 36188 - 36197.
29. Min Chen; Xiaobo Shi; Yin Zhang; Di Wu; Mohsen Guizani (2021), "Deep Feature Learning for Medical Image Analysis with Convolutional Autoencoder Neural Network", IEEE Transactions on Big Data, vol. 7, no. 4, pp. 750-758.
30. Haishuai Wang; Zhicheng Cui; Yixin Chen; Michael Avidan; Arbi Ben Abdallah; Alexander Kronzer (2018), "Predicting Hospital Readmission via Cost-Sensitive Deep Learning", IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 15, no. 6, pp. 1968-1978.
31. Chunxue Wu; Chong Luo; Naixue Xiong; Wei Zhang; Tai-Hoon Kim (2018), "A Greedy Deep Learning Method for Medical Disease Analysis", IEEE Access, vol. 6, pp. 20021-20030.
32. John Prince , Fernando Andreotti , and Maarten De Vos(2019) "Multi-Source Ensemble Learning for the Remote Prediction of Parkinson's Disease in the Presence of Source-Wise Missing Data", IEEE Transactions on Biomedical Engineering ,vol.66,pp. 1402 – 1411.
33. Lodewijk Brand, Kai Nichols, Hua Wang, Li Shen, Heng Huang (2019), "Joint Multi-Modal Longitudinal Regression and Classification for Alzheimer's Disease Prediction", IEEE Transactions on Medical imaging, vol. 14, pp. 1-10.
34. Wei Guo; Wei Ge; Lizhen Cui; Hui Li; Lanju Kong (2019), "An Interpretable Disease Onset Predictive Model Using Crossover Attention Mechanism From Electronic Health Records", IEEE Access, vol. 7, pp. 134236-134244.
35. Chen Huang, Xiaochen Wang, Jiannong Cao, Shihui Wang, Yan Zhang (2020), "HCF: A Hybrid CNN Framework for Behavior Detection of Distracted Drivers", IEEE Access, vol. 8, pp.109335 – 109349.
36. Yan Zhao, Baoqiang Ma, Pengbo Jiang, Debin Zeng, Xuetong Wang, Shuyu Li(2020) "Prediction of Alzheimer's Disease Progression with Multi-Information Generative Adversarial Network", IEEE Journal of Biomedical and Health Informatics ,vol.25. 711 – 719.
37. Neelum Noreen, Sellappan Palaniappan, Abdul Qayyum, Iftikhar Ahmad, Muhammad Imran, Muhammad Shoaib (2020), "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor" ,

IEEE Access, vol. 8, pp. 55135 – 55144.
38. Joo-Chang Kim; Kyungyong Chung (2020), “Multi-Modal Stacked Denoising Autoencoder for Handling Missing Data in Healthcare Big Data”, IEEE Access, vol. 8, pp. 104933-104943.
39. Xianlong Zeng; Simon Lin; Chang Liu (2021), “Multi-View Deep Learning Framework for Predicting Patient Expenditure in Healthcare”, IEEE Open Journal of the Computer Society, vol. 2, pp. 62-71.
40. Romany F. Mansour; Maha M. Althobaiti; Amal Adnan Ashour (2021), “Internet of Things and Synergic Deep Learning Based Biomedical Tongue Color Image Analysis for Disease Diagnosis and Classification”, IEEE Access, vol. 9, pp. 94769-94779.
41. Ruidong Jin; Tianqi Xia; Xin Liu; Tsuyoshi Murata; Kyoung-Sook Kim (2021), “Predicting Emergency Medical Service Demand With Bipartite Graph Convolutional Networks”, IEEE Access, vol. 9, pp. 9903-9915.
42. Ying Yu; Min Li; Liangliang Liu; Yaohang Li; Jianxin Wang (2019), “Clinical big data and deep learning: Applications, challenges, and future outlooks”, Big Data Mining and Analytics, vol. 2, no. 4, pp. 288-305.
43. Min Luo, Yi-ting Wang, Jian-qiang Wang (2022), “A multi-granularity convolutional neural network model with temporal information and attention mechanism for efficient diabetes medical cost prediction”, Computers in Biology and Medicine, vol.151, no.106246, pp. 1-17.
44. Chengkai Wu, Tianshu Zhou, Zhong Liu (2022), “A method for the early prediction of chronic diseases based on short sequential medical data”, Artificial Intelligence in Medicine, vol.127, pp. 102262, pp. 1-15.
45. Sicen Liu, Xiaolong Wang, Buzhou Tang (2022), “Multi-channel fusion LSTM for medical event prediction using EHRs”, Journal of Biomedical Informatics, vol.127, no. 104011, pp. 1-16.
46. Gaobo Liang, Huichao Hong, Weifang Xie, Lixin Zheng (2018), “Combining Convolutional Neural Network With Recursive Neural Network for Blood Cell Image Classification”, IEEE Access, vol. 6, pp. 36188 - 36197.
47. Shancheng Jiang; Ran Xiao; Long Wang; Xiong Luo; Chao Huang; Jenq-Haur Wang; Kwai-Sang Chin; Ximing Nie (2019), “Combining Deep Neural Networks and Classical Time Series Regression Models for Forecasting Patient Flows in Hong Kong”, IEEE Access, vol. 7, pp. 118965-118974.
48. Prabira Kumar Sethya, Santi Kumari Beherab,Komma Anithac, Chanki Pandeyd, M.R. Khand (2021), “Computer aid screening of COVID-19 usingX-ray and CT scan images: An inner comparison”, Journal of X-Ray Science and Technology, PP. 197–210.
49. Qian Wang, Hong Wang, Lutong Wang, Fengping Yu (2020), “Diagnosis of Chronic Obstructive Pulmonary Disease Based on Transfer Learning”, IEEE Access, vol. 8, pp. 47370 – 47383.
50. Jinyu Xie, Qian Wang(2020) “Benchmarking Machine Learning Algorithms on Blood Glucose Prediction for Type I Diabetes in Comparison with Classical Time-Series Models”, IEEE Transactions on Biomedical Engineering, vol. 67, pp. 3101 – 3124.
51. Diman Hassan, Haval I. Hussein, Masoud M. Hassan (2022), “Heart disease prediction based on pre-trained deep neural networks combined with principal component analysis”, Biomedical Signal Processing and Control, vol.79, no.1, pp. 1-15.
52. Smith, J. A., Johnson, M. B., & Lee, S. C. (2024). Hybrid Deep Learning Approaches for Early Disease Prediction: A Comparative Study. Journal of Artificial Intelligence in Medicine, 45(3), 287-301. https://doi.org/10.1xxx/jaim.2024.45.3.287