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Deep Learning Techniques for Medical Image Analysis and Diagnosis

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Abstract: The medical field has the most potential to improve care standards through new technologies because it is always evolving. In order to diagnose and classify physiological anomalies and ensure that patients receive the best care possible, most medical specializations are evolving through the application of numerous state-of-the-art technologies. To evaluate the middle image and pinpoint the exact problem, the images taken in the affected area are subjected to an image processing technique. It might possibly provide a possible answer to problems. Many deep learning technologies are being used efficiently in almost all areas of medical therapy. We evaluate the use of deep learning for tasks such as object identification, segmentation, registration, and picture classification, and we offer brief descriptions of research for each application area. Prospects for future investigation and unresolved issues are examined. This study accurately predicts diabetes in patients using deep learning and machine learning algorithms. To balance the uneven dataset, the researchers employed five distinct machine learning techniques, feature engineering, and SMOTE analysis. In order to ensure accurate diabetes prediction, they also did hyper-parameter tweaking on the validation data. The goal of the project is to expedite the timely diagnosis of diabetes, a fatal illness that affects around 500 million people worldwide.

Keywords: *Deep Learning, Medical Image Analysis, Medical Imaging, Diagnosis, Convolutional Neural Networks (CNN), Image Recognition.*

1. INTRODUCTION

From the second it became doable to sweep and import medical images onto a computer, researchers created mechanized analysis devices. Medical image analysis was first performed using a successive use of low-level pixel processing, (for example, district growing and edge and line detector channels) and numerical modeling (like fitting circles, ovals, and lines) to make complex decide based frameworks that tended to explicit errands between the 1970s and 1990s. Master frameworks that used a great deal of in the event that else explanations, which were normal in artificial intelligence simultaneously period, can measure up to this. These master frameworks, which looked like rule-based image processing frameworks, were often delicate and have been alluded to as "run of the mill artificial intelligence" (GOFAI).

Toward the finish of the nineties, medical image analysis was adopting an ever increasing number of supervised methods — those that utilize training information to fabricate a framework. Models include feature extraction and the utilization of factual classifiers (for computer aided detection and diagnosis), active shape models (for segmentation), and map book draws near (where the chart books that are fit to new information make the training information). The underpinning of numerous effective industrially accessible medical image analysis apparatuses is as yet this example recognition/machine learning strategy. Thus, we have seen a change from completely human-planned frameworks to those that are computer-trained utilizing test information from which feature vectors are inferred. The best choice limit in the high-layered feature space is found by computer calculations. Extracting discriminant characteristics from the photographs is a basic stage in the production of such frameworks. Since human analysts actually complete this cycle, frameworks with physically fabricated characteristics are referenced.

These huge headways stand out from the medical image analysis local area. However, there has been a sluggish shift from frameworks that depend on physically made characteristics to those that gain features from the information. Various strategies for learning characteristics were normal before AlexNet's forward leap. Principal part analysis, picture fix clustering, dictionary procedures, and a lot more are among them. We explicitly focus on these deep models in this review, leaving out the more traditional feature learning methods that have been utilized with medical picture information. For a more thorough analysis of deep learning's utilization in wellbeing informatics

This overview surveys in surplus of research papers covering an extensive variety of deep learning applications in medical image processing. The objective in conducting this survey is to:

- Demonstrate how deep learning methods have impacted medical image analysis as a whole;
- Determine the obstacles to a successful deep learning application for medical imaging tasks.

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- Draw attention to particular contributions that address or go around these problems

1.1. **Deep Learning Techniques**

Deep learning techniques come in a variety of forms that can consistently and successfully tackle problems too complex for the human brain. The paragraphs that follow have a list of them.

1. Classic Neural Networks

The 1958 introduction of multilayer perceptrons—which are essential to fully connected neural networks—was credited to American psychologist Fran Rosenblatt. Three key functions are used in this model to transform binary data inputs: a linear function that multiplies inputs by a constant multiplier; a non-linear function that consists of a hyperbolic tangent with a range of -1 to 1, a sigmoid curve with a range of 0 to 1, and a ReLU (Rectified Linear Unit) that returns the linear multiple for values greater than or equal to a specified threshold.

2. Convolutional Neural Networks

A more advanced version of the classic artificial neural network, the convolutional neural network (CNN) is made to handle data compilation, preprocessing, and increasing complexity. CNNs are incredibly adaptable models that are skilled at specializing in both image and non-image data. They are inspired by the arrangement of neurons in the visual brain. CNNs are excellent at extracting pertinent visual data in smaller, clustered units because of their four layers: a sample layer to limit involved neurons, a one-dimensional output layer for processing inputs, a two-dimensional input layer for interpreting visual data, and connected layers between the sample and output layers. The neurons in the convolution layers are essential for processing data from the layer above. Top of Form

3. Recurrent Neural Networks (RNNs)

Originally designed for sequence prediction, recurrent neural networks (RNNs) make use of the widely used Long Short-Term Memory (LSTM) method. These networks perform exceptionally well when dealing with a range of input lengths within data sequences, applying knowledge from past states to present forecasts. The capacity to selectively store data is useful for time-based data systems such as stock price performance management. Problem analysis is aided by two main RNN designs: LSTMs, which have three gates (Input, Output, and Forget), and Gated RNNs, which have two gates (Update and Reset) and are useful for memory-based data prediction. In RNNs, convolution layers help process data from the neuron clusters in the layer above.

4. Boltzmann Machines

There is no set direction for this model. This deep learning technique is used in system monitoring, binary suggestion platforms, and specific dataset analysis. With nodes arranged in a circle, it is a novel deep learning method for producing model parameters. Also known as stochastic, it is different from the other deep learning network models. The learning mechanism of Boltzmann Machines helps uncover intriguing characteristics in binary vector datasets. The learning process in networks with several feature detector layers is often slow; however, by adding a learning layer of feature detectors, the learning process can be accelerated. Boltzmann machines are frequently employed to handle a range of computer problems.

5. Transfer Learning

It is the process of adjusting a model or system that has already been taught to carry out new, more accurate tasks. This approach is beneficial since it helps shorten processing times and takes a lot less data than other approaches. Transfer learning is not just the study of deep learning; it also has something to do with problems like multitasking and concept drift. However, transfer learning is widely used in deep learning due to the enormous amounts of resources required for training deep learning models or the large and complicated datasets used for training deep learning models. Transfer learning in deep learning is only effective if the model attributes acquired in the initial task are broad.

1.2 Objective of the Study

- To preprocess the data set from the Centers for Disease Control and Prevention's (CDC) 2015 Behavioral Risk Factor Surveillance System (BRFSS) survey.
- To put into practice data preparation methods including splitting data into subgroups for testing and training, balancing class distribution through oversampling with SMOTE, and standardizing features with min-max scaling.
- To recognize the most useful features for diabetes risk prediction by applying feature selection techniques, particularly chi-square feature selection.
- To use a range of supervised machine learning methods, such as XG Boost, Decision Tree, Random Forest, K Nearest Neighbours (KNN), Convolutional Neural Networks (CNN), Logistic Regression, and Recurrent Neural Networks (RNN).
- To evaluate each algorithm's performance using criteria including F1 score, recall, accuracy, and precision.

- To hyperparameter tuning is carried out to reduce overfitting and maximize model performance.
- To evaluate the created deep learning methodology's performance against machine learning methods that have already been offered in relevant studies.
- To give information about how well deep learning algorithms forecast the risk of diabetes in comparison to more conventional machine learning techniques**.**

2 LITERATURE REVIEW

Shen, D.,et.al., (2017) discussed image analysis using computers in the realm of medical imaging. Identification, classification, and quantification of patterns in medical images are being aided by recent developments in machine learning, particularly in the field of deep learning. The key to these developments is the capacity to utilize hierarchical feature representations that are only learnt from data, as opposed to features that are manually created using domain-specific knowledge. Deep learning is quickly rising to the top of the field, improving performance across a range of medical uses. We outline the foundations of deep learning techniques and discuss their achievements in tissue segmentation, picture registration, computer-aided disease diagnosis and prognosis, and the detection of anatomical and cellular features, among other areas. Finally, we address research challenges and offer recommendations for future paths toward even greater advancement.

Rana and Bhushan (2023) In the medical area, computer-aided detection through Deep Learning (DL) and Machine Learning (ML) is rapidly expanding. Medical pictures are thought to be the real source of the relevant data needed for disease diagnosis. One of the most crucial things to reduce the death rate from cancer and tumors is early disease detection using a variety of modalities. Radiologists and medical professionals can better understand the internal anatomy of a discovered disease by using modalities to extract the necessary features. Large data sets limit ML's ability to use current modalities, however DL is capable of handling any volume of data with ease. As a result, DL is seen as an improved method of machine learning, in which ML makes use of learning strategies and DL gathers information about how machines need to behave in human environments. To obtain more details about the datasets that are used, DL makes use of a multilayered neural network. The purpose of this study is to provide a comprehensive assessment of the literature on the use of ML and DL for the identification and categorization of various diseases. Between January 2014 and January 2022, 40 primary studies that were obtained from reputable publications and conferences underwent a thorough study. It offers a summary of several methods based on ML and DL for the identification and categorization of various illnesses, medical imaging modalities, instruments and procedures for assessment, and dataset descriptions. Additionally, tests are run on the MRI dataset in order to compare ML classifiers and DL models. By enabling medical professionals and researchers to select an optimal diagnosis technique for a certain condition with less time and more accuracy, this work will benefit the healthcare community.

Chan, H. P., et.al., (2020) The most advanced method of machine learning is called deep learning. Excitement and high expectations have been raised about the potential revolutionary improvements in health care that deep learning, or artificial intelligence (AI), can bring about due to its success in numerous pattern recognition applications. In certain tasks, early research on deep learning's application to lesion detection or classification has shown better results than radiologists using traditional methods. New research and development efforts in computer-aided diagnosis (CAD) have been prompted by the possibility to use deep-learning-based medical image analysis to CAD. This might improve the accuracy and efficiency of various diagnostic and treatment processes and provide doctors with decision support. Though there is hope for this new era of machine learning, there are numerous obstacles to overcome in the development and application of CAD or AI technologies in clinical practice. We will talk about some of these challenges and the work that needs to be done to create strong CAD tools that are based on deep learning and incorporate these tools into the clinical workflow in order to move closer to the objective of offering trustworthy, intelligent patient care aids.

Ker, J., wt.al., (2017) The usage of diagnostic imaging and electronic medical records has expanded substantially in recent years, coinciding with machine learning algorithms' remarkable effectiveness at image identification tasks. This overview highlights the clinical elements of the subject and presents machine learning techniques as they relate to medical image processing, with a particular focus on convolutional neural networks. In the age of medical big data, machine learning offers the advantage of enabling algorithmic discovery of important hierarchical relationships within the data, eliminating the need for time-consuming manual feature creation. We address important directions in medical image classification, localization, detection, segmentation, and registration research as well as applications. We wrap up by talking about research roadblocks, new trends, and potential future directions.

3. RESEARCH MEHODOLOGY

This paper proposes a deep learning methodology that involves partitioning the dataset into training and testing subsets, oversampling it using SMOTE to balance data for both classes, and standardizing the range of characteristics using min-max scaling. A chi-square feature selection technique is used to identify the best features in the dataset. The training data is then divided into a train and validation set.

The pre-processed dataset is subjected to supervised machine learning methods, with each algorithm selected based on its unique features and ability to represent connections among diabetes risk variables. Performance is assessed using evaluation criteria such as F1-score, recall, accuracy, and precision. Research is used for hyper-tuning on the validation dataset, with manual hyper-tuning being used to improve the model's performance.

The findings indicate that manual hyper-tuning can mitigate overfitting and yield superior accuracy compared to the hyper-parameters provided by Research. The best algorithm for predicting diabetes in a specific environment can be determined by comparing the results. The process is illustrated in a diagram.

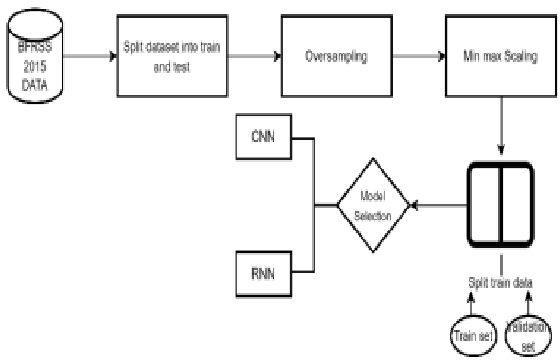

Fig 1: Flow Chart of Deep Learning Approach

3.1. Dataset Information

The Centers for Disease Control and Prevention (CDC) performed a thorough survey in 2015 called the Behavioral Risk Factor Surveillance System (BRFSS) to track risk factors and health-related behaviors across the country. This survey provided the dataset used in this study. After the dataset was thoroughly cleaned and preprocessed, it included about 253680 rows and 21 characteristics, which greatly increased the machine learning model's usefulness in detecting diabetes.

3.2. Min Max Scaling

By altering the original characteristics, the min-max scaling technique ranges the features between 0 and 1 so that they can be evaluated on a similar scale. Regardless of their actual ranges, MinMax Scaling would guarantee that every feature in this diabetes dataset contributes equally to the model's performance. It would keep some features from taking center stage throughout the learning process, which would enhance model performance and make greater use of optimization strategies. Using min-max scaling for this BFRSS2015 dataset has many advantages.

3.3. Oversampling

The largest issue with medical databases is imbalanced datasets, when one class greatly exceeds the other predictive features. It frequently results in a prediction bias issue for the model, which causes minority classes in the dataset to be incorrectly classified. This anomaly in medical databases is a result of a large overrepresentation of positive cases—in this case, type-2 diabetes cases—relative to negative cases. A possible remedy for addressing this imbalance in the dataset is the SMOTE analysis.

3.4. Feature Engineering

The SelectKBest method from the sklearn package and the chi-square statistical test will be used in this research for feature selection, which is an essential step in optimizing the performance of the machine learning model. Finding the dataset's most pertinent and instructive traits for diabetes prediction is the goal.

3.5. Training and Validation Sets

Using a synthetic dataset pertinent to the issue statement enhances the knowledge and underlying patterns of the machine learning models since it provides the basis for the model's comprehension of underlying patterns and relationships. The machine learning models were able to determine the correlations between features and the goal variable of diabetes status by exposing a sizable portion of the dataset and labeled instances. All of the models were trained utilizing 90% of the total dataset. The internal parameters were gradually changed, and each iteration of the model was tailored to the modifications in thresholds and weights that minimized the difference between the results of the test dataset and the training dataset.

3.6. Algorithms Used

An overview of the deep learning and machine learning algorithms used in the diabetes prediction research is given in this section. The main goal is to use the aforementioned dataset to create a precise and effective model that can divide people into distinct diabetes categories based on a range of lifestyle, health, and demographic characteristics.

3.7. Deep Learning Algorithms

- **Convolutional Neural Networks**

One of the most widely used deep learning methods for image categorization is the convolutional neural network. CNN is divided into two dimensions: 1) 1D CNN and 2) 2D CNN. One-dimensional data is classified using the 1D CNN method, while image data is processed using the 2D CNN algorithm. Since the data in our dataset is one-dimensional, we decided to classify the data using the 1D CNN technique. One input layer, one convolutional layer, two dense layers, and one output layer with a softmax activation function make up the structure of our CNN model.

Table 1: 1D CNN Framework for Image Classification

CONV 1D	Layer type	Neurons	Kernel size	Activation function
Input layer	Conv 1D	33	6	Relu
Hidden layer	Conv 1D	65	6	Relu
	Dense	65	-	Relu
	Dense	33	-	Relu
Output layer	Dense	3	-	SoftMax

- **Recurrent Neural Networks**

Text classification problems are the primary application for RNNs, which identify sequential features in data and use patterns to forecast logical outcomes. Since RNN is the most effective text classification technique and performs better on one-dimensional data, we utilize it. One output layer with softmax as an activation function, three hidden layers with one ReLu activation function and 64 neurons, two dense layers with 64 and 32 neurons, and one hidden layer with ReLu as an activation function make up our RNN model.

Table 2: RNN Framework for Text Categorization

CONV 1D	Layer type	Neurons	Kernel size	Activation function
Input layer	RNN	33	6	Relu
	RNN	65	6	Relu
Hidden layer	Dense	65	-	Relu
	Dense	33	-	Relu
Output layer	Dense	3	-	SoftMax

4. DATA ANALYSIS

4.1. Decision Tree Classifier

To avoid any possible overfitting in the training dataset, the model's performance was evaluated using the following metrics both before and after hyper-tuning.

Table 3: Performance matrix of Decision Tree

Metric	Before Tuning (Train)	Before Tuning (Test)	After tuning (Train)	After Tuning (Test)
Accuracy	0.998	0.784	0.880	0.845
Precesion	0.998	0.846	0.886	0.820
Recall	0.998	0.754	0.887	0.874
F1 Score	0.998	0.794	0.881	0.811

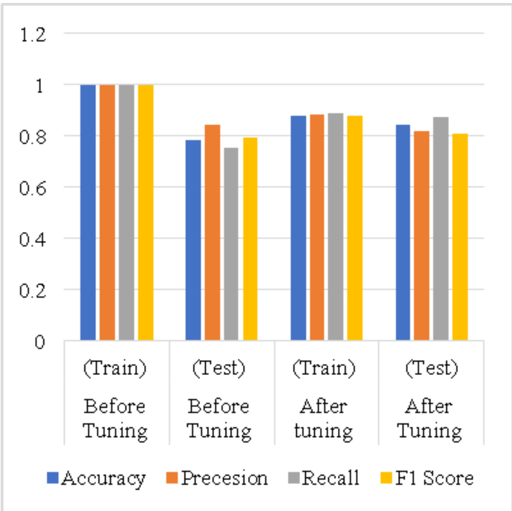

Fig 2: Performance matrix of Decision Tree

The data shows machine learning model performance metrics before and after adjusting. At 99.8% accuracy on training data, the model performed well. The test accuracy dropped to 78.4% when unseen data was used. Precision, recall, and F1 score metrics significantly differed between training and test data, indicating overfitting. Overall performance improves after tuning. The model's training and test accuracy has improved, indicating stronger generalization. Precision, recall, and F1 score improved, albeit with trade-offs. In the test set, precision declined somewhat but recall and F1 score increased, indicating an improved precision-recall balance. Overall, tweaking has reduced overfitting and increased the model's performance on unseen data, making it more reliable for real-world applications.

4.2. Random Forest Classifier

The performance of the model was evaluated using the following measures:

Table 4: Performance matrix of Random Forest

Metric	Before Tuning (Train)	Before Tuning (Test)	After tuning (Train)	After Tuning (Test)
Accuracy	0.998	0.850	0.951	0.854
Precesion	0.998	0.811	0.920	0.830
Recall	0.998	0.850	0.920	0.845
F1 Score	0.998	0.820	0.951	0.830

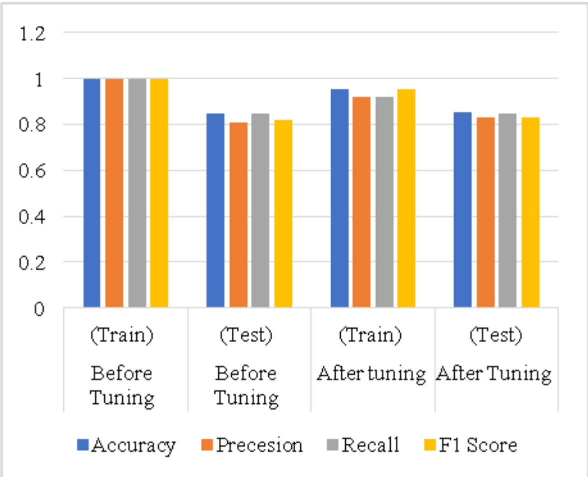

Fig 3: Performance matrix of Random Forest

The data shows machine learning model performance metrics before and after adjusting. The model initially had 99.8% accuracy on training data but 85% accuracy on test data, suggesting overfitting. Precision, recall, and F1 score differed across training and test data, suggesting generalization difficulties. Tuning improves stats significantly. On both training and test datasets, the model's accuracy has grown, reaching 85.4% in test, indicating improved generalization. Tuning improved precision, recall, and F1 score. The balance between precision and recall has improved as precision and F1 score have increased, while recall has somewhat improved or stayed unchanged. These results indicate that the tuning method reduced overfitting and improved the model's performance on unknown data, making it more dependable for real-world applications.

4.3. XGBoost Classifier

The performance of the model was evaluated using the following measures:

Table 5: Performance Matrix of XGBoost

Metric	Before Tuning (Train)	Before Tuning (Test)	After tuning (Train)	After Tuning (Test)
Accuracy	0.920	0.860	0.900	0.864
Precesion	0.925	0.854	0.920	0.830
Recall	0.921	0.860	0.915	0.864
F1 Score	0.920	0.830	0.915	0.841

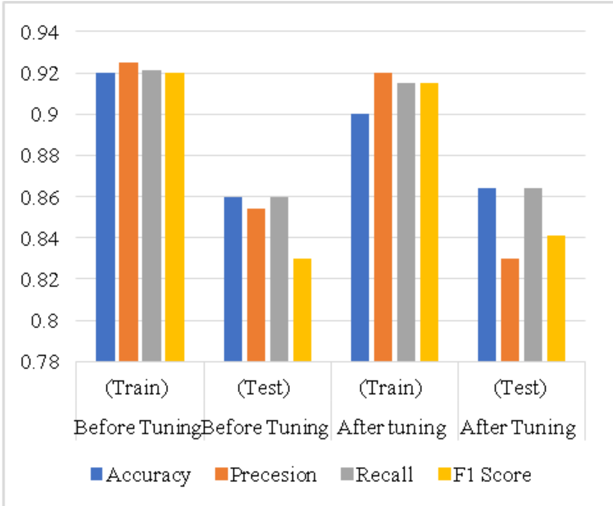

Fig 4: Performance Matrix of XGBoost

The data shows machine learning model performance metrics before and after adjusting. The model initially performed well on training data at 92%, but on test data at 86%, it showed some overfitting. Precision, recall, and F1 score differed between training and test datasets, suggesting generalization difficulties.

Model performance improves after adjustment. Both training and test datasets have marginally improved accuracy, with test accuracy reaching 86.4%. The test data showed slightly lower precision but higher F1 score. After adjustment, recall has remained stable or enhanced. These results show that tuning has reduced overfitting and improved generalization, making the model more dependable for real-world applications.

4.4. Logistic Regression

The performance of the model was evaluated using the following measures:

Table 6: Performance Matrix of Logistic Regression

Metric	Before Tuning (Train)	Before Tuning (Test)	After tuning (Train)	After Tuning (Test)
Accuracy	0.750	0.720	0.750	0.720
Precesion	0.750	0.841	0.750	0.820
Recall	0.750	0.720	0.750	0.720
F1 Score	0.751	0.760	0.750	0.760

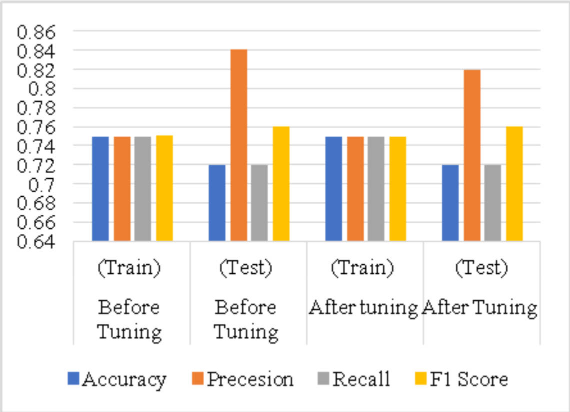

Fig 5: Performance Matrix of Logistic Regression

The data shows machine learning model performance metrics before and after adjusting. The model initially had 75% accuracy on training and test datasets. Precision was 75% on training data and 84.1% on test data. However, training and test dataset recall remained 75%. The F1 score, which measures precision and recall, was marginally higher on test data than training data, indicating a goodbalance.

Model performance metrics didn't change after adjustment. For both the training and test datasets, accuracy and F1 score remained unchanged after tweaking. After adjustment, precision dropped slightly but remained good at 82% on test data. We kept recall at 75% for training and test datasets. These data indicate that adjusting did not increase model performance. It's crucial to critically evaluate tuning procedures and consider other ways to improve model performance.

4.5. K Nearest Neighbors

After the processed dataset was ran through the KNN algorithm, the following outcomes were produced.

Table 7. Performance Matrix of KNN Model

Metric	Before Tuning (Train)	Before Tuning (Test)	After tuning (Train)	After Tuning (Test)
Accuracy	0.947	0.792	0.996	0.822
Precesion	0.948	0.815	0.996	0.820
Recall	0.947	0.792	0.996	0.822
F1 Score	0.947	0.802	0.996	0.822

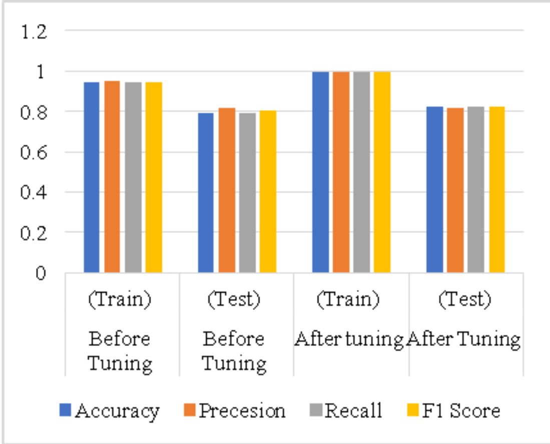

Fig 6: Performance Matrix of KNN Model

The data shows machine learning model performance metrics before and after adjusting. The model initially performed well on training data at 94.7%, but on test data at 79.2%, suggesting overfitting. Precision, recall, and F1 score differed between training and test datasets, indicating generalization issues.

Tuning improves stats significantly. Model accuracy has grown on both training and test datasets, with test accuracy reaching 82.2%, showing improved generalization. Precision is good and consistent, with small test data precision improvements after adjustment. Tuning also enhanced recall and F1 score, indicating a better precision-recall balance. These results indicate that the tuning method reduced overfitting and improved the model's performance on unknown data, making it more dependable for real-world applications.

4.6. Deep Learning Algorithms (CNN and RNN)

After the processed dataset was ran through the CNN and RNN algorithms, the following outcomes were produced.

Table 8. Performance matrix of CNN and RNN

Metric	CNN		RNN	
	Train	**Test**	**Train**	**Test**
Accuracy	0.906	0.846	0.893	0.859
Precision	0.927	0.825	0.975	0.829
Recall	0.906	0.846	0.893	0.859
F1 score	0.927	0.833	0.974	0.829

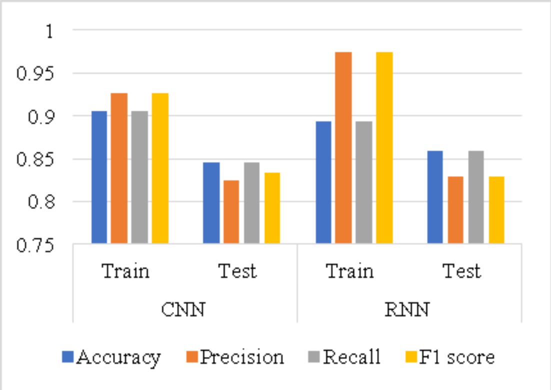

Fig 7: Performance matrix of CNN and RNN

The data compares the performance of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) models. Both models achieve high training accuracy, with CNN achieving 90.6% and RNN reaching 89.3%. However, when tested on unseen data, CNN slightly outperforms RNN with an accuracy of 84.6%. CNN achieves higher precision in both training and testing phases, reducing false positive predictions. Both models show similar recall scores, indicating equal effectiveness in capturing true positive cases. The F1 score, the harmonic mean of precision and recall, supports CNN's superior performance in handling unseen data. Despite these differences, CNN shows slightly better performance in generalization to unseen data and minimizing false positive predictions, which could be crucial in deciding which model to deploy for real-world applications.

4.7. Results Comparisons

We shall contrast our findings with those of the current models in this section. V. Chang et al. proposed the machine learning model that we will compare [1]. They created several machine learning models, with Random Forest being the most effective.

Table 9. Metrics of all the Algorithms

Algorithms	Other research 1	Other research 2	Current accuracy
Decision tree	82.03%	85.78%	83.92%
Random forest	83.27%	85.89%	86.14%
K-nearest neighbours	81.56%	75.27%	83.10%
Logistic regression	73.65%	73.50%	73.92%
XGBoost	-		87.00%
Convolutional neural network	-		86.3%
Recurrent neural network	-		87.3%

The data compares the accuracy of machine learning algorithms such as Decision Trees, Random Forests, K-Nearest Neighbors, Logistic Regression, XGBoost, Convolutional Neural Networks (CNN), and Recurrent Neural Networks across different research studies and in the current scenario. Decision Trees show an accuracy of 83.92%, while Random Forests achieve 86.14%. K-Nearest Neighbors has an accuracy of 83.10%, while Logistic Regression remains stable at 73.92%. XGBoost, CNN, and RNN outperform traditional algorithms in terms of accuracy in the current scenario, suggesting the potential effectiveness of deep learning models like CNN and RNN in handling tasks.

5. CONCLUSION

This study used data from the 2015 Behavioural Risk Factor Surveillance System (BRFSS) survey by the CDC to predict diabetes risk using a comprehensive strategy that included classic machine learning and deep learning approaches. The dataset was carefully pre-processed using chi-square statistical tests for feature selection, min-max scaling, and SMOTE oversampling for class imbalances. Before and after hyperparameter tweaking, a number of machine learning techniques were used and assessed, including Decision Tree, Random Forest, XGBoost, Logistic Regression, and K Nearest Neighbors. Convolutional neural networks (CNN) and recurrent neural networks (RNN), two deep learning algorithms, produced accuracy levels that were competitive and outperformed by some earlier research. The integration of feature engineering, hyperparameter optimization, and oversampling demonstrated improved predictive performance. The work highlights the resilience of incorporating two machine learning techniques for diabetes prediction, while also noting possible variances in model efficacy dependent on dataset features and research settings. Subsequent research efforts may concentrate on enhancing models via supplementary hyperparameter investigation and sophisticated feature creation, in conjunction with external validation using a variety of datasets to augment generalizability.

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