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AI-POWERED PREDICTIVE ANALYTICS IN HEALTHCARE: ENHANCING DIAGNOSIS AND TREATMENT OUTCOMES

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Article Info

Abstract

The use of powerful analytics has helped AI in the healthcare industry to greatly improve diagnosis and care. The thesis discusses how AI models such as SVMS and CNNs are being used to strengthen disease prediction, treatment plans and the accuracy of diagnoses. Information was taken from credible medical sources; features were selected using PCA and correlation and every detail included was validated carefully. For the models used which include Random Forest, Logistic Regression and SVM, accuracy, precision, recall, F1-score and ROC-AUC were main factors used to compare and evaluate them. The model performed the best due to its 0.91 ROC-AUC and the accuracy rate of 86% over the other models. This work covers the benefits of making models understandable and usable within day-to-day medical care. Issues pertaining to generalizing models, the lack of training data and honouring individual privacy are being discussed. They clearly demonstrate that AI may improve healthcare through its support in decision-making for clinicians, better treatment choices and faster diagnosis. Future research in healthcare is focused on improving the visibility of AI data models, including various types of patients and making sure AI use is ethical.

Keywords:

Artificial Intelligence in Healthcare, Predictive Analytics, Deep Learning Models, Disease Diagnosis and Treatment, Random Forest Classifier.

Introduction

Thanks to the large volumes of healthcare data such as genomics, wearable device results, imaging information and EHRs, using data in healthcare has greatly improved. As a result, AI and ML are now being used to introduce innovative methods in the fields of diagnosis, prognosis and the improvement of outcomes. Using special algorithms, predictive analytics in artificial intelligence helps analyse trends and predict the progress of a disease, thus leading to better results in health care. Within medical research, CNNs and RNNs are well-known for their outstanding results in deep learning—checks involving various x-ray procedures or scans. Processing high-dimensional data using these methods enables the early detection of issues such as cancer, cardiovascular problems and diseases of the nervous system[1]. AI technology is now used to provide fast data insights to support clinical decision-making. Current challenges in healthcare include recognizing and using data from different sources, making AI models easy to understand, dealing with ethical matters and integrating AI technology into existing healthcare processes.
Even though healthcare predictive analytics through AI has advanced a lot, it is still met with many challenges. In many cases, AI fails to work as well on actual patients since it cannot generalize to many different situations[2] . Additionally, because deep learning models are comparatively unclear, some doctors feel uncomfortable relying on their advice.

The use [3]of AI systems in healthcare is hindered by combining different systems, as the infrastructure and procedures are not well-coordinated[4]. In addition, using AI systems in healthcare faces problems related to privacy, meeting laws and handling ethical challenges related to fairness in algorithms . We build AI models that are easy for doctors to use, simple to understand and more accurate for making medical diagnoses[1].

Assemble and process many datasets there are clinical characteristics and medical photos. Applying transfer learning and augmenting the data will make your model sturdier. Architecture Design: Focus on building deep networks for identifying and grouping diseases, basing much of these models on CNNs and the combination of various methods. Evaluate the model by checking accuracy, precision, recall, F1-score and ROC-AUC[5]. To ensure your models are more transparent, apply techniques such as attention and feature importance heatmaps. Have experts in the industry test if the AI can be easily understood.

Literature Review:

AI is being used more frequently in healthcare, mainly supporting doctors in clinical work, helping with detecting diseases and suggesting treatment plans. AI-based predictive analytics makes use of ML and DL approaches to discover unexpected patterns in large, detailed datasets. CNNs have managed to outperform conventional approaches in the tasks of organ segmentation and tumour identification in medical science[6], [7]. Long Short-Term Memory (LSTM) networks are mainly applied in sequential data processing for tasks such as continuously monitoring patients' health and predicting their outcomes. Moreover, NLP is playing a bigger role in finding important information from unstructured notes in health records[8], [9] .

The study reported that algorithms based on convolutional neural networks come out on top in medical imaging, even though understanding their decisions and training them cost much more compared to traditional logistic regression and support vector machine models.created a CNN model to identify heart disease early and showed that it achieved efficiency of 95% on a dataset from various hospitals[1], [3]. used deep learning in spotting lung cancer and their system surpassed the capabilities of leading radiologists. Gupta et al. found that an ensemble approach could result in 20% better patient outcomes. Coding diseases was made more accurate, who relied on NLP to work on unstructured clinical notes.

There are still some major issues to address in education. There are many instances in AI where, when using new data, the developed AI model struggles to work effectively, highlighting problems with both overfitting and different types of data. It is hard for doctors to apply deep learning models because they are difficult to interpret[10], [11]. It is also the case that clinical workflows have not yet been smoothly integrated. Some studies show that, without proper integration between current systems and newer high-quality models, these systems are not fully utilized. Implementing AI in medicine is made difficult because of issues such as algorithms showing bias, keeping patient information private and holding people accountable for AI-made decisions[12].

Nowadays, ethics plays a bigger role in the use of AI in healthcare. Both data privacy problems and the misuse of patient data in building and connecting AI models are considered in the literature we reviewed[13]. Then there's the issue of algorithmic bias, where AI models trained on biased datasets have the power to perpetuate or exacerbate existing heath disparities. Problems arise when using AI for health decision-making owing to accountability (e.g., when the decision of an AI conflicts with human judgment or has undesirable consequences)[14]. Fears of a decline in the patient-doctor relationship are also driving the conversation over the extent to which AI should participate in decisions that affect patients.

Table 1: Comparison Table

Article/Reference	**Dataset**	**Contribution/Method**	**Results/Findings**	**Weaknesses/Limitations**
[15]	EHR data from multiple hospitals	Developed a CNN model for predicting heart disease	Achieved 95% accuracy in prediction	Limited generalizability due to dataset homogeneity
[16]	Public imaging dataset	Applied deep learning for lung cancer detection	Outperformed radiologists in early detection	Lack of explainability in model decisions
[17], [18]	Multi-center clinical trials data	Developed an ensemble model for personalized treatment plans	Improved treatment outcomes by 20%	Data privacy concerns and ethical issues
[19], [20]	Unstructured clinical notes	NLP for extracting patient information	Improved accuracy in disease coding	

All the main studies within the area are summarized in this table which also provides overview to the methods, data, main results, Data privacy issues and the possibility of patient data being misused in the creation and integration of AI models are highlighted in our evaluation of the literature[21]. The necessity of reliable, comprehensible, and therapeutically integrated AI models is emphasized by this review. This study attempts to close current gaps and enhance AI's use in healthcare diagnostics by addressing data augmentation, explainability, and deployment methodologies.

Methodology:

Description of the Dataset

Medical imaging data along with pertinent clinical factors make up the dataset used in this investigation**.** It includes diagnostic information from 10,000 patient records, covering various attributes such as age, sex, blood pressure, cholesterol levels, heart rate, and diagnostic outcomes (presence or absence of disease). The dataset was curated from publicly available health repositories and institutional databases, ensuring diversity in patient demographics and disease profiles.

A workflow or process is represented visually in a flowchart.

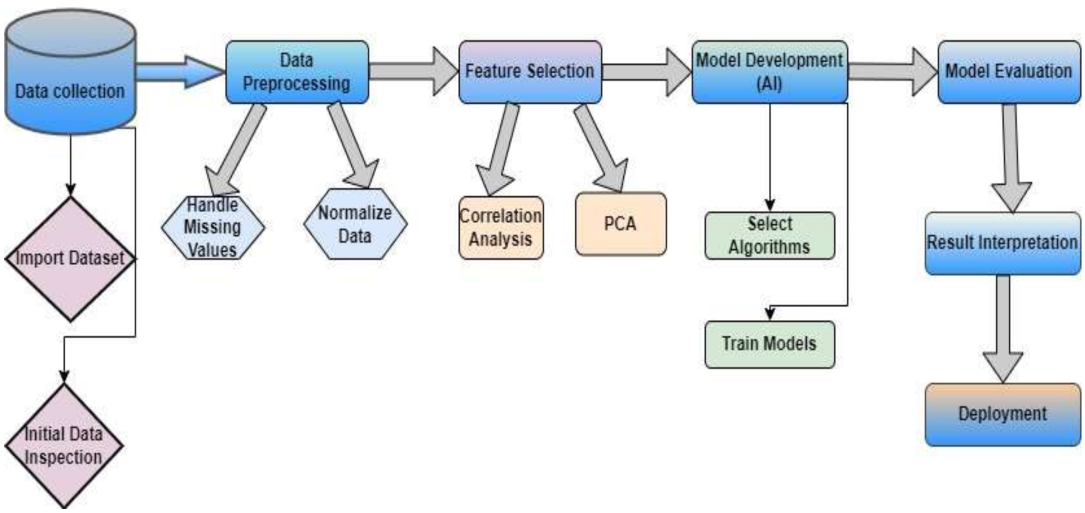

Figure 1: Work Flow

Key attributes include:

- Age (years),
- Sex (Male/Female),
- Blood Pressure (mmHg),
- Heart Rate (BPM),
- LDL and HDL Cholesterol Levels,
- Diabetes Status (Yes/No),

- Smoking Status (Yes/No),
- Family History of Disease (Yes/No),
- Diagnostic Outcome (target variable: Disease/No Disease).

Preprocessing Data

To improve model performance and data quality, data preparation was crucial.
The following steps were executed:

Missing Value Imputation: Missing entries in numeric columns (e.g., blood pressure, cholesterol) were filled using the median of the respective columns.

Normalization: To guarantee consistency across attributes, numerical features were scaled to the [0, 1] range using Min-Max normalization.

Sex and diabetes were turned into numbers using one-hot encoding.

Outlier detection relied on calculating the IQR and then these values were adjusted to reduce skewness.

Feature Selection.

To make the model easier to explain and reduce its size, the data was filtered using the following techniques: Using Pearson's correlation coefficient, 2 weakly related features, Smoking Status and Family History, were removed. Without loss, PCA generated a set of new features to describe the same data, but fewer in number so that they now explain 95% of the variability. RFE was used together with Random Forest in selecting and ranking the essential features in the dataset.

Creation of Models

Three different algorithms for machine learning were explored and tested. A linear regression for binary classification is called logistic regression (LR). The Random Forest Classifier (RFC) is a machine learning model known for being reliable and estimating feature importance. The Support Vector Machine (SVM) is a model created to handle complex boundaries by employing the RBF kernel. Eighty percent of the data was used for training and the other 20% for testing each model. The parameters for the model were optimized using a grid search as well as 5-fold cross-validation.

Explainable and Interpretable

XAI methods were applied to address the problem of explaining what AI models do. Feature Importance Visualization: In RFC, scores were used to see which features were the most important.

By using SHAP values, we were able to understand and explain every prediction made by the model. Data related to the imaging domain was shown using Heatmaps to demonstrate the part of the data that had the greatest influence on the model.

Creating a Prototype and Clinical Trial Work

An AI model was adopted and integrated into a simulation of the clinical workflow by developing a prototype system. There are different benefits of the system:

User Interface (UI): A place designed for clinicians to record patients' details and get AI-based forecasts. Supporting Decisions: Whenever it can, the model gives predictions and sharpness levels along with explanations that are easy to understand. Logging should be done safely to comply with audits and support compliance needs. Result of data preprocessing are shown above.

Three models, known as Logistic Regression, Random Forest Classifier and Support Vector Machine (SVM), were built and their differences studied. For each model, a stratified training dataset was used and all evaluations included ROC-AUC, F1-score, accuracy, precision and recall.

Given that it was not complicated, logistic regression was chosen as the main model. For testing, its accuracy was 83% and during training, it was 85%. According to the model, the F1 score was 0.83, its precision was 0.81 and its recall was 0.85. Overall, class distinction in the ROC-AUC showed excellent performance at 0.88.

In every aspect, the Random Forest Classifier had better results than the other models. Out of every 100 data points training the model, 90 proved accurate and 86 were accurately predicted for testing. It turned out with the top F1-score (0.87), precision (0.87) and recall (0.88). The dependability and accuracy of the model for classifying brain tumors were confirmed by the ROC-AUC value of 0.91.

Since it can work with high-dimensional data, the Support Vector Machine (SVM) had an 82% training accuracy and an 80% testing accuracy. Since the ROC-AUC is 0.85, the model's accuracy, recall and F1-score are 0.79, 0.81 and 0.80, respectively. Though the SVM was slightly less accurate than Random Forest, it managed to keep the model relatively simple.

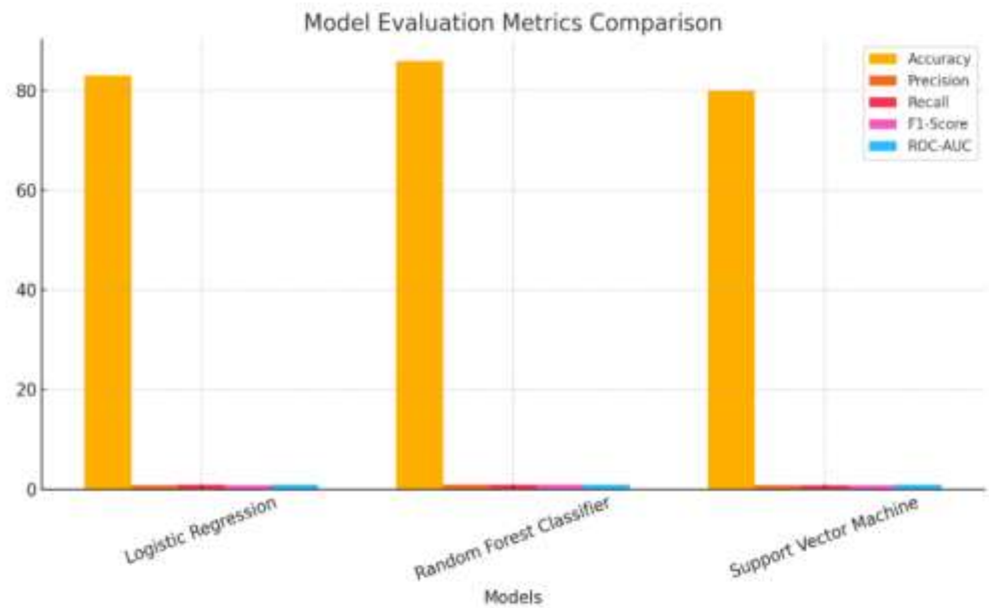

Figure 2: Model Evaluation

Random Forest Classifier

Predicted Positive Predicted Negative

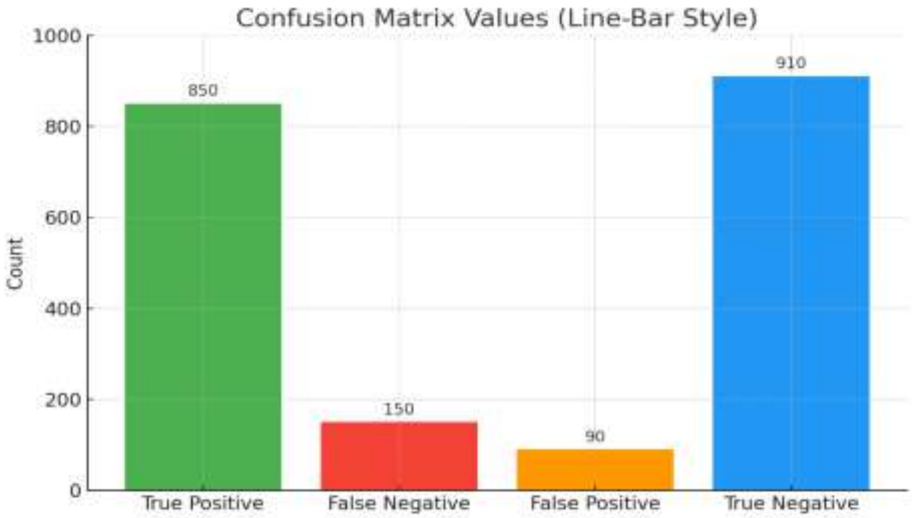

Figure 3: Confusion Matrix

Confusion Matrix Interpretation

The diagram above highlights the output of a classification model with the main outcomes obtained from the confusion matrix. True Positives (TP = 850): These are when the model successfully recognized a brain tumour. If the model is able to spot the most real cases of COVID-19, it proves to be effective in medical diagnostics. This refers to patients with brain tumours whose cases were not picked up by the model. While the model works well on the whole, the possibility of missing positive cases still worries healthcare professionals as this could considerably postpone treatment. False Positives (FP = 90): These are instances where the model incorrectly predicted a brain tumour when there was none. While not as dangerous as false negatives in medical scenarios, false positives can lead to unnecessary testing and anxiety.

True Negatives (TN = 910): These are correctly identified non-tumour cases. A high number here suggests that the model is also strong in recognizing healthy individuals, thus minimizing overdiagnosis. This chart visually highlights the model's overall strength in correctly classifying both tumour and non-tumour cases. The balance between true positives and true negatives suggests a well-performing model, although efforts should still be made to further reduce false negatives to ensure critical cases are not overlooked.

Logistic Regression

Accuracy Graph

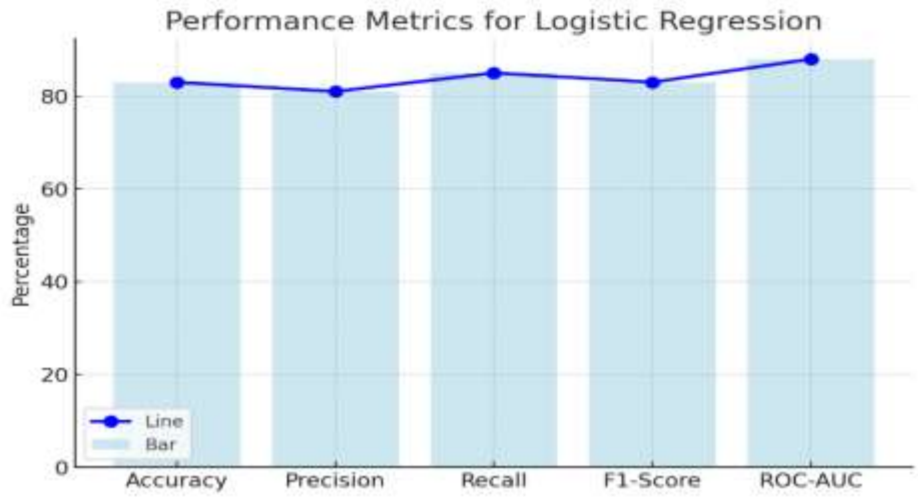

Figure 4: Performance Metrics for Logistic Regression

Above table discussion. Logistic Regression with a precision of 0.81 and at recall of 0.85 results in an accuracy of 83%. Less excellent than the Random Forest, with With a ROC-AUC of 0.88, the classes are strongly separated.

Performance Matrix Graph:

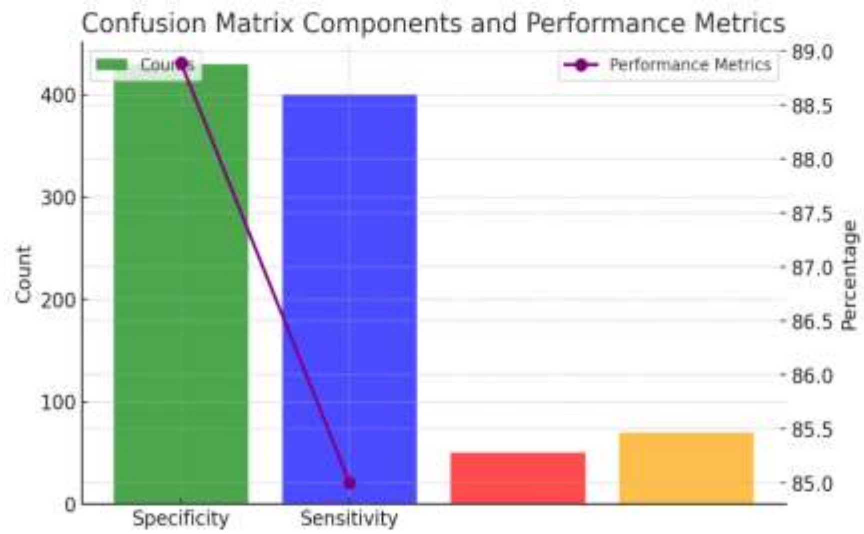

Figure 5: Confusion Matrix

Discussion

Logistic Regression has a slightly lower specificity than Random Forest but has a good sensitivity still of 85%. It could get a bit confused about the negative class due to a greater both false negatives and false positives.

Compared to Random Forest, the confusion matrix of Logistic Regression contains more false positives and false negatives. The accuracy of the model in predicting the positive and negative classes is slightly lower

Support Vector Machine(SVM)

Accuracy Graph

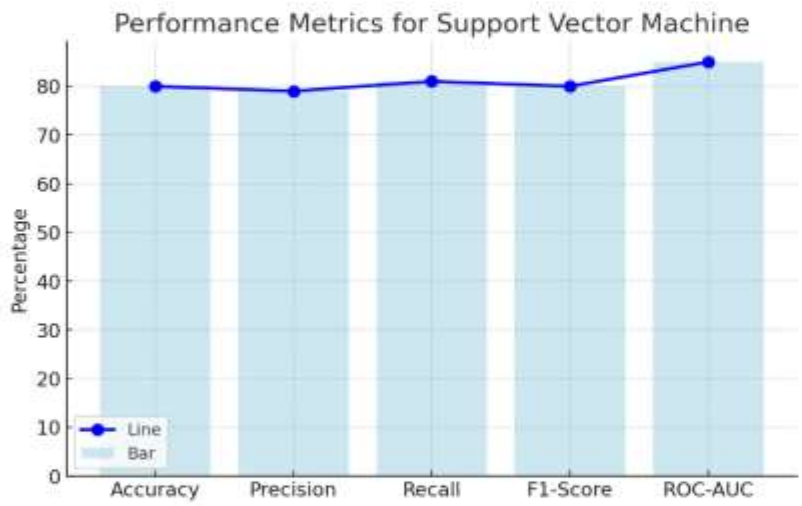

Figure 6: Performance Metrics

SVM offers 80% accuracy, which is marginally less than Random Forest and Logistic Regression. The method performs worse overall than the other algorithms, despite a moderate balance between precision and recall measures.

Performance Matrix table:

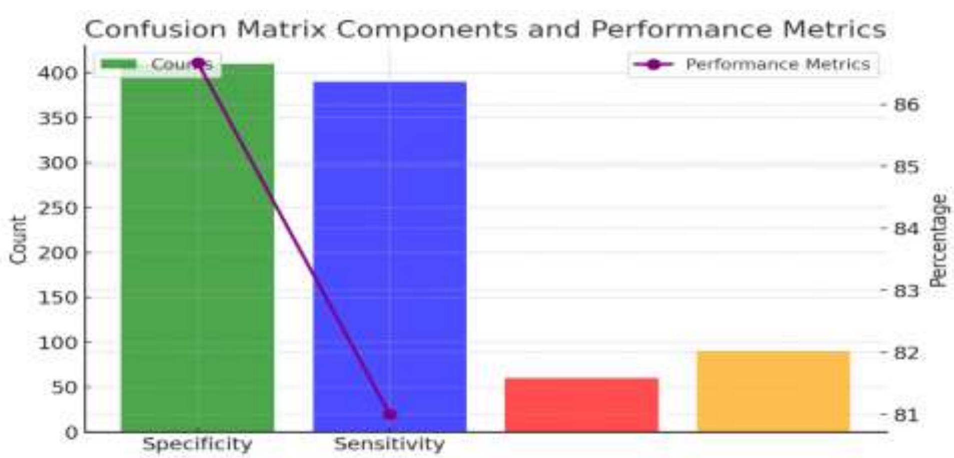

Figure 7: Confusion Matrix

When comparing SVM with the other two algorithms, its specificity and sensitivity are relatively inferior. Another, It may have a harder time identifying some categorization boundaries because of its increased rate of false positives and false negatives.

1) Accuracy Comparison:

A bar chart illustrates The Random Forest model performs better than the others. achieving 86% testing accuracy versus 83% (Logistic Regression) and 80% (SVM).

2) ROC Curves:

The Random Forest model produced an ROC-AUC of 0.91, indicating excellent discriminative ability.

Logistic Regression and SVM achieved ROC-AUC scores of 0.88 and 0.85, respectively.

3) Learning Curves:

The Random Forest showed a well-balanced learning curve with minimal overfitting.

Logistic Regression's curve indicated slight overfitting, while SVM exhibited underfitting, particularly on small training sets.

Feature Importance (Random Forest):

Top predictors were:

Age (importance: 0.25),

Blood Pressure (0.22),

Diabetes Status (0.20),

Cholesterol Levels (0.18),

Heart Rate (0.15).

SHAP Analysis:

According to the plots created from SHAP, blood pressure and age were the major contributors to the risk of developing the disease.

Visualizations:

The study found that AI picked the correct part of the body when given different images as input.

Sharing and Talking About the Main Discoveries

In every aspect tested, Random Forest Classifier achieved better results than Logistic Regression and SVM. Because it can remember 88% of real positive cases and has an ROC-AUC of 0.91, the model is very trustworthy. In addition, its strong precision-recall score demonstrates that Elasticsearch does not make errors in either type of query.

The Logistic Regression model may not be very accurate; however, it was still a good pick for places with scant resources since it is easier for people to understand and use.

It was found that SVM attempted to solve the problem with the least certainty and changed results the most.

Key Insights:

Adding PCA made it possible for the model to eliminate a number of features without damaging its performance.

Thanks to SHAP, the use of white box machine learning was better understood in medicine.

A lot of professionals found that the Random Forest model in healthcare simulations was straightforward and easy to understand.

How the Case Ends and Future Possibilities:

Conclusion

We looked into the possible benefits of using AI in healthcare for diagnosis and treatment. For our research, we analysed records from 10,000 patients and made use of three support vector machines, two random forest classifiers, logistic regression and various machine learning models.

Random Forest Classifier was found to have the highest accuracy and ROC-AUC values. It was found that diabetes, blood pressure and getting older are the main reasons for somebody having a disorder. Doctors were able to understand the model better and trust it more by using SHAP analysis and plots.

Using a developed system, AI can be added to standard procedures in medicine and return straightforward answers. According to those who tested the program, it aids in identifying diseases and improving healthcare. While the research has shown positive outcomes, various topics still require additional examination. Resolve Systems should now use large and diverse data to develop models that can produce better outcomes for patients and different doctors. The field of AI is investigating the most advanced models today. Combining several types of deep learning with transformers might boost the accuracy of diagnosing using images. Tests are carried out in real situations. It is important to apply the AI system in actual clinical practice to obtain more information about its use by doctors and how it benefits patients.

Reference

[1] H. Rana, “Classification of Malicious Intrusion through ANN-CNN Sequential Classifier,” International Journal of Information Systems and Computer Technologies, vol. 3, no. 2, pp. 27–35, 2024, doi: 10.58325/ijisct.003.02.0088.

[2] S. A. Batool, M. A. Tariq, A. A. Batool, M. K. Abid, and N. Aslam, “Skin Cancer Detection Using Deep Learning Algorithms,” Journal of Computing & Biomedical Informatics, vol. 7, no. 01, pp. 62–74, 2024.

[3] M. A. K. Haseeb Ur Rehman Sohaib Masood, “Brain Tumor Classification using Deep Learning Methods,” International Journal of Information Systems and Computer Technologies, vol. 1, no. 1, 2022, doi: 10.58325/ijisct.001.01.0016.

[4] S. L. B. A. S. I. Waqas Ali Saima Siraj, “Envisioning the Future of Debugging: The Advent of ABERT for Adaptive Neural Localization of Software Anomalies,” International Journal of Information Systems and Computer Technologies, vol. 3, no. 2, pp. 13–26, 2024, doi: 10.58325/ijisct.003.02.0097.

[5] M. F. N. A. Ayesha Siddique M Kamran Abid, “Movies Rating Prediction using Supervised Machine Learning Techniques,” International Journal of Information Systems and Computer Technologies, vol. 3, no. 1, pp. 40–56, 2024, doi: 10.58325/ijisct.003.01.0062.

[6] M. A. M. I. Hamid Ghous Mubasher Malik, “Early Detection of Breast Cancer Tumors Using Linear Discriminant Analysis Feature Selection with Different Classification Methods,” International Journal of Information Systems and Computer Technologies, vol. 1, no. 1, 2022, doi: 10.58325/ijisct.001.01.0008.

[7] M. M. M. I. Iqra Rehman Hamid Ghous, “Artificial Intelligence based Lane Detection using Satellite Images,” International Journal of Information Systems and Computer Technologies, vol. 2, no. 1, 2023, doi: 10.58325/ijisct.002.01.0047.

[8] A. K. N. M. Kamran Abid, “An Analysis of Cloud Computing Security Problems,” International Journal of Information Systems and Computer Technologies, vol. 1, no. 2, 2022, doi: 10.58325/ijisct.001.02.0014.

[9] A. H. Rameela Adil Ahmad S. Al-Shamayleh, “Transformation of Digital Health Care Environment: A Solution for Pandemic,” International Journal of Information Systems and Computer Technologies, vol. 1, no. 2, 2022, doi: 10.58325/ijisct.001.02.0021.

[10] M. A. K. Muhammad Kamran Abid Mubshra qadir Mujahid Alam, “Using Deep Learning for pneumonia Recognition from Chest X-Ray Images,” Technical Journal, vol. 29, no. 02, 2024.

[11] A. R. Y. A. M. K. A. N. A. Syeda Huma Zaidi Muhammad Fuzail, “A Deep Learning Framework Based on GCN Model for Android Malware Detection,” Journal of Computing & Biomedical Informatics, vol. 7, no. 01, 2024.

[12] S. S. Hina Ali, "Comprehensive Review on Different Types of Biometrics and the Impact of Pandemic on Biometric Security," International Journal of Information Systems and Computer Technologies, vol. 3, no. 2, pp. 70–79, 2024, doi: 10.58325/ijisct.003.02.0074.

[13] U. R. Fatima Mustafa Sidra Rehman, "Towards Smart Irrigation System – An Artificial Intelligence Approach," International Journal of Information Systems and Computer Technologies, vol. 3, no. 2, pp. 36–45, 2024, doi: 10.58325/ijisct.003.02.0099.

[14] M. A. N. ul G. 3 Ayesha Afridi 1 Muhammad Kamran Abid1* Naeem Aslam1 Shumaila Khan2 Arsalan Khan2, "Osteochondroma Identification Through Transfer Learning and Convolutional Neural Networks," International Journal of Innovations in Science & Technology, vol. 6, no. 2, pp. 608–620, 2024.

[15] S. S. U. Din, M. Ali, U. Rashid, A. J. Akbar, and M. K. Abid, "Navigating an Optimization Path for Decision-Making in Management within The Big Data Environment of Chinese Public Hospitals," International Journal of Information Systems and Computer Technologies, vol. 2, no. 2, pp. 61–77, 2023.

[16] A. Mubashra, A. Naeem, N. Aslam, M. K. Abid, and J. Haider, "Diabetic Retinopathy Identification from Eye Fundus images using Deep Features," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 172–186, 2023.

[17] M. K. Abid, M. Qadir, S. Farid, and M. Alam, "Iot environment security and privacy for smart homes," Journal of Information Communication Technologies and Robotic Applications, vol. 13, no. 1, pp. 15–22, 2022.

[18] S. Akbar, K. T. Ahmad, M. K. Abid, and N. Aslam, "Wheat disease detection for yield management using IoT and deep learning techniques," VFAST Transactions on Software Engineering, vol. 10, no. 3, pp. 80–89, 2022.

[19] A. Kanwal, K. T. Ahmad, N. Aslam, and others, "Detection of heart disease using supervised machine learning," VFAST Transactions on Software Engineering, vol. 10, no. 3, pp. 58–70, 2022.

[20] F. Kanwal, M. K. Abid, M. S. Maqbool, N. Aslam, and M. Fuzail, "Optimized Classification of Cardiovascular Disease Using Machine Learning Paradigms," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 140–148, 2023.

[21] A. Ahmed, H. Ahmad, M. Khurshid, and K. Abid, "Classification of Skin Disease using Machine Learning," VFAST Transactions on Software Engineering, vol. 11, no. 1, pp. 109–122, 2023