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AI DRIVEN RABBIT OPTIMIZER FOR EMERGENCY DEPARTMENT SURVEILLANCE AND MEDICAL DATA ANALYSIS

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Abstract: Amid the escalating prevalence of heart diseases globally, this project addresses the urgent need for more accurate prediction methods. Heart-related conditions are on the rise, necessitating advanced tools for early detection and intervention. The significance of this project lies in its potential to revolutionize heart disease prediction. Accurate models can significantly impact public health by enabling timely and targeted interventions, thereby mitigating the growing burden of cardiovascular illnesses. Focused on enhancing heart disease prediction, the project employs state-of-the-art machine learning algorithms and feature engineering techniques. By assessing models like ARO with VNBLR, Neural Network, Decision Tree, SVM, GBDT, and Naive Bayes, we aim to identify the most effective approach for accurate predictions. This project benefits healthcare professionals, researchers, and individuals concerned about heart health. Accurate prediction models provide a proactive approach to healthcare, enabling personalized interventions and improving outcomes for individuals at risk of heart diseases. With heart diseases becoming a leading cause of mortality worldwide, the outcomes of this project have the potential to contribute significantly to the global health landscape. Timely and accurate predictions empower healthcare systems to address the growing challenges posed by cardiovascular conditions. As an extension to the project, we have incorporated advanced ensemble learning techniques to enhance the predictive capabilities of our heart disease prediction model. Utilizing a stacking classifier, composed of Random Forest and Decision Tree classifiers, along with a final LightGBM classifier, enables the model to harness the strengths of different algorithms for improved accuracy. Additionally, a voting classifier, combining AdaBoost and Random Forest classifiers, enhances model robustness through a soft voting mechanism.

Index terms - *Medical data classification, emergency departments, KSA hospitals, feature selection, machine learning.*

1. INTRODUCTION

Recently, the healthcare field is generating data from a lot of patients and facilities. By using this data, clinicians can easily anticipate better techniques for treatment and boost the medical field [1]. One significant use of the python structure encourages computing facilities to extract useful insights from the data over the healthcare domain. Disease diagnosis is determining the disease through symptoms of persons [2]. The challenging issue in the diagnosis is some signs and symptoms were non-specific. Machine learning (ML) helps to forecast the disease diagnosis depending on the prior training data. Several scientists have made different ML techniques to work well to diagnose different diseases [3]. ML presents the capability for machines to learn without being specifically programmed. Evolving a model by ML techniques can forecast an initial-stage disease diagnosis and render solutions. Effective treatment and initial diagnosis are the optimal way to reduce death rates [4]. Hence, many clinical scientists have adopted new methods for predicting diseases depending on ML techniques.

Artificial intelligence (AI) is defined as human intelligence executed by machines [5]. In computer science, it is considered as the capability of machines to emulate intellectual behaviour by itself, utilizing ML [6]. In medicine, AI applications are growing rapidly. In the medical field, AI is the use of automated diagnosis and the treatment of victims who need care. Generally, ML is classified as unsupervised (which deals with clustering of various groups for specific interventions) or supervised (composed of output parameters that are estimated from input variables) [7]. ML can determine complex methods, expose innovative ideas to doctors, and extract medical knowledge. In medical practice, ML prediction algorithms can point out improved rules in deciding on individual patient care. The infusion of such methods in drug prescription can offer new medical openings in pathology recognition and save clinicians [8]. The medical data quality can probably be enhanced with ML methods, save medical costs and lessen fluctuations in patient rates. Consequently, these methods are often utilized for investigating diagnostic analysis than other classical techniques [9]. Early recognition and potential treatments will be the only solution for reducing the mortality rates caused by chronic disease (CD). Thus, many medical scientists were attracted towards the innovative technologies of prediction approaches in forecasting diseases [10].

2. LITERATURE SURVEY

[1] The paper, " E-healthcare monitoring system using IoT with machine learning approaches," addresses Internet of Things (IoT) is an emerging technology that is drastically improving with many new enhancements in medical and health domains. IoT Health wearable devices are taking new challenges by upgrading with innovative technology and resources. Using health wearable devices, in/out patient's health status can be monitored periodically and regularly. This paper introduces an IoT application framework E-Healthcare Monitoring System (EHMS) integrated with Machine learning (ML) techniques to design an advanced automation system. Using this system it will connect, monitor and decisions making for proper diagnosis.

[2] The paper, " IoT for smart cities: Machine learning approaches in smart healthcare—A review," addresses the Smart city is a collective term for technologies and concepts that are directed toward making cities efficient, technologically more advanced, greener and more socially inclusive. These concepts include technical, economic and social innovations. This term has been tossed around by various actors in politics, business, administration and urban planning since the 2000s to establish tech-based changes and innovations in urban areas. The idea of the smart city is used in conjunction with the utilization of digital technologies and at the same time represents a reaction to the economic, social and political challenges that post-industrial societies are confronted with at the start of the new millennium. The key focus is on dealing with challenges faced by urban society, such as environmental pollution, demographic change, population growth, healthcare, the financial crisis or scarcity of resources. In a broader sense, the term also includes non-technical innovations that make urban life more sustainable. So far, the idea of using IoT-based sensor networks for healthcare applications is a promising one with the potential of minimizing inefficiencies

in the existing infrastructure. A machine learning approach is key to successful implementation of the IoT-powered wireless sensor networks for this purpose since there is large amount of data to be handled intelligently. Throughout this paper, it will be discussed in detail how AI-powered IoT and WSNs are applied in the healthcare sector. This research will be a baseline study for understanding the role of the IoT in smart cities, in particular in the healthcare sector, for future research works.

[5] The paper titled " Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine" addresses to implement effective precision medicine with enhanced ability to positively impact patient outcomes and provide real-time decision support, it is important to harness the power of electronic health records by integrating disparate data sources and discovering patient-specific patterns of disease progression. Useful analytic tools, technologies, databases, and approaches are required to augment networking and interoperability of clinical, laboratory and public health systems, as well as addressing ethical and social issues related to the privacy and protection of healthcare data with effective balance. Developing multifunctional machine learning platforms for clinical data extraction, aggregation, management and analysis can support clinicians by efficiently stratifying subjects to understand specific scenarios and optimize decision-making. Implementation of artificial intelligence in healthcare is a compelling vision that has the potential in leading to the significant improvements for achieving the goals of providing real-time, better personalized and population medicine at lower costs. In this study, we focused on analyzing and discussing various published artificial intelligence and machine learning solutions, approaches and perspectives, aiming to advance academic solutions in paving the way for a new data-centric era of discovery in healthcare.

[6] The paper titled " A comprehensive survey on machine learning-based big data analytics for IoT-enabled smart healthcare system" addresses The outbreak of chronic diseases such as COVID-19 has made a renewed call for providing urgent healthcare facilities to the citizens across the globe. The recent pandemic exposes the shortcomings of traditional healthcare system, i.e., hospitals and clinics alone are not capable to cope with this situation. One of the major technology that aids contemporary healthcare solutions is the smart and connected wearables. The advancement in Internet of Things (IoT) has enabled these wearables to collect data on an unprecedented scale. These wearables gather context-oriented information related to our physical, behavioural and psychological health. The big data generated by wearables and other healthcare devices of IoT is a challenging task to manage that can negatively affect the inference process at the decision centres. Applying big data analytics for mining information, extracting knowledge and making predictions/inferences has recently attracted significant attention. Machine learning is another area of research that has successfully been applied to solve various networking problems such as routing, traffic engineering, resource allocation, and security. Recently, we have seen a surge in the application of ML-based techniques for the improvement of various IoT applications. Although, big data analytics and machine learning are extensively researched, there is a lack of study that exclusively focus on the evolution of ML-based techniques for big data analysis in the IoT healthcare sector. In this paper, we have presented a comprehensive review on the application of machine learning techniques for big data analysis in the healthcare sector. Furthermore, strength and weaknesses of existing techniques along with various research challenges are highlighted. Our study

will provide an insight for healthcare practitioners and government agencies to keep themselves well-equipped with the latest trends in ML-based big data analytics for smart healthcare.

[5] The paper " A review on the role of machine learning in enabling IoT based healthcare applications" addresses the The Internet of Things (IoT) is playing a vital role in the rapid automation of the healthcare sector. The branch of IoT dedicated towards medical science is at times termed as Healthcare Internet of Things (H-IoT). The key elements of all H-IoT applications are data gathering and processing. Due to the large amount of data involved in healthcare, and the enormous value that accurate predictions hold, the integration of machine learning (ML) algorithms into H-IoT is imperative. This paper aims to serve both as a compilation as well as a review of the various state of the art applications of ML algorithms currently being integrated with H-IoT. Some of the most widely used ML algorithms have been briefly introduced and their use in various H-IoT applications has been analyzed in terms of their advantages, scope, and possible improvements. Applications have been divided into the domains of diagnosis, prognosis and spread control, assistive systems, monitoring, and logistics. In healthcare, practical use of a model requires it to be highly accurate and to have ample measures against security attacks. The applications of ML algorithms in H-IoT discussed in this paper have shown experimental evidence of accuracy and practical usability. The constraints and drawbacks of each of these applications have also been described.

3. METHODOLOGY

i) Proposed Work:

The proposed system integrates diverse algorithms, including Artificial Rabbit Optimizer with Decision Tree, VNBLR, Neural Network, Decision Tree, Support Vector Machine, and GBDT. Each algorithm is applied, with the aim of identifying the best-performing one for optimal medical data classification in Emergency Departments, enhancing decision-making processes in healthcare. And also, we have incorporated advanced ensemble learning techniques to enhance the predictive capabilities of our heart disease prediction model. Utilizing a stacking classifier, composed of Random Forest and Decision Tree classifiers, along with a final LightGBM classifier, enables the model to harness the strengths of different algorithms for improved accuracy. Additionally, a voting classifier, combining AdaBoost and Random Forest classifiers, enhances model robustness through a soft voting mechanism. Furthermore, to facilitate user testing and engagement, we have implemented a user-friendly Flask framework integrated with SQLite, allowing users to sign up and sign in. This extension not only enhances the model's predictive performance but also provides a practical platform for real-world user interactions and feedback.

ii) System Architecture:

In the data collection phase, diverse patient health data is gathered from sources like wearable devices and medical records. Subsequently, data preprocessing involves cleaning, formatting, and standardizing the collected data for consistency. In the feature engineering stage, the system leverages the Artificial Rabbit Optimizer (ARO) to construct and refine features tailored for the subsequent model building and training. ARO's optimization capabilities are employed to enhance the effectiveness of the features designed for algorithms such as Decision Tree, VNBLR, ANN, SVM, GBDT, Naive Bayes, as well as extensions like stacking classifier and voting classifier. This collaborative effort ensures that the features are finely tuned and optimized, contributing to the overall accuracy and predictive power of the healthcare data classification system. Model evaluation assesses the performance of these models; with the most accurate one selected for integration with Emergency Department systems. Real-time monitoring then utilizes continuous data for timely alerts and informed decision-making within the healthcare data classification system.

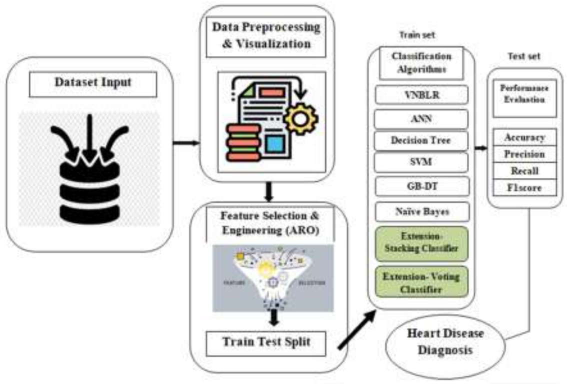

Fig 1 Proposed architecture

iii) Dataset collection:

The Cleveland dataset is a well-known dataset used in the field of machine learning, particularly in the context of heart disease diagnosis. It originated from the Cleveland Heart Disease Database and contains various attributes related to patient health, aiding in the prediction of heart disease.

On the other hand, the Statlog dataset refers to a collection of datasets compiled for statistical and machine learning research. These datasets cover a range of domains and are commonly used for benchmarking and evaluating the performance of machine learning algorithms. The specific content and characteristics of the Statlog datasets can vary based on the particular dataset under consideration.

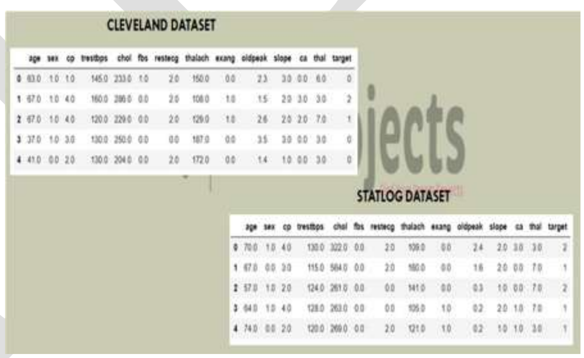

Fig 2 Dataset

iv) Data Processing:

Data processing involves transforming raw data into valuable information for businesses. Generally, data scientists process data, which includes collecting, organizing, cleaning, verifying, analyzing, and converting it into readable formats such as graphs or documents. Data processing can be done using three methods i.e., manual, mechanical, and electronic. The aim is to increase the value of information and facilitate decision-making. This enables businesses to improve their operations and make timely strategic decisions. Automated data processing solutions, such as computer software programming, play a significant role in this. It can help turn large amounts of data, including big data, into meaningful insights for quality management and decision-making.

v) Feature selection:

Feature selection is the process of isolating the most consistent, non-redundant, and relevant features to use in model construction. Methodically reducing the size of datasets is important as the size and variety of datasets continue to grow. The main goal of feature selection is to improve the performance of a predictive model and reduce the computational cost of modeling.

Feature selection, one of the main components of feature engineering, is the process of selecting the most important features to input in machine learning algorithms. Feature selection techniques are employed to reduce the number of input variables by eliminating redundant or irrelevant features and narrowing down the set of features to those most relevant to the machine learning model. The main benefits of performing feature selection in advance, rather than letting the machine learning model figure out which features are most important.

vi) Algorithms:

In this project, the **Artificial Rabbit Optimizer (ARO)** algorithm is used to pick the best features for the task. The algorithm mimics how rabbits decide whether to explore for food or hide based on their energy levels. If the energy factor (A(t)) is less than or equal to 1, the rabbits hide randomly; otherwise, they explore for food. The energy factor is calculated using a formula, and during exploration, rabbits find food randomly based on the positions of others. This approach is inspired by the survival tactics of real rabbits in nature.

```python
from FS.aro import jfs   # change this to switch algorithm

X = X.values
y = y.values

feat  = np.asarray(X)
label = np.asarray(y)

# split data into train & validation (70 -- 30)
xtrain, xtest, ytrain, ytest = train_test_split(feat, label, test_size=0.3, stratify=label)
fold = {'xt':xtrain, 'yt':ytrain, 'xv':xtest, 'yv':ytest}

# parameter
k    = 5     # k-value
N    = 5    # number of particles
T    = 5   # maximum number of iterations
opts = {'k':k, 'fold':fold, 'N':N, 'T':T}

# perform feature selection
fmdl = jfs(feat, label, opts)
sf   = fmdl['sf']
```

Fig 3 Artificial Rabbit Optimizer

Neural Networks, inspired by the human brain, consist of layers of interconnected neurons. Through training, weights are adjusted to capture complex patterns in healthcare data, making them adept at identifying intricate relationships and predicting disease outcomes. Their ability to handle non-linearities and extract meaningful features aligns well with the nuanced nature of medical data, making Neural Networks a suitable choice for this project in healthcare data classification.

```
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(random_state=1, max_iter=300)
mlp.fit(X_train, y_train)

y_pred    = mlp.predict(X_test)

mlp_acc = accuracy_score(y_pred, y_test)
mlp_prec = precision_score(y_pred, y_test,average='weighted')
mlp_rec = recall_score(y_pred, y_test,average='weighted')
mlp_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('ANN',mlp_acc,mlp_prec,mlp_rec,mlp_f1)
```

Fig 4 ANN

Decision Trees, employed in this project, operate by recursively splitting data based on features, creating a tree-like structure for decision-making. Their interpretability and effectiveness in handling both categorical and numerical healthcare data make Decision Trees suitable for this project. The transparent decision process aids clinicians in understanding and trusting the model's predictions, crucial in healthcare applications where interpretability is paramount for informed decision-making.

```
from sklearn.tree import DecisionTreeClassifier
tree = DecisionTreeClassifier()

tree.fit(X_train, y_train)

y_pred    = tree.predict(X_test)

dt_acc = accuracy_score(y_pred, y_test)
dt_prec = precision_score(y_pred, y_test,average='weighted')
dt_rec = recall_score(y_pred, y_test,average='weighted')
dt_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('ARO with ML',dt_acc,dt_prec,dt_rec,dt_f1)
```

Fig 5 Decision tree

Support Vector Machine (SVM), chosen for this project, seeks to find a hyperplane that effectively separates classes in high-dimensional spaces. Its capability to handle complex relationships within healthcare data and identify intricate patterns makes SVM a suitable choice. By maximizing the margin between different classes, SVM aims for robust generalization, ensuring reliable predictions for diverse medical scenarios. The flexibility and efficacy of SVM in capturing nuanced relationships in healthcare data contribute to its selection for this project in medical data classification.

```
]: from sklearn.svm import SVC
   svm = SVC(probability=True)
   svm.fit(X_train, y_train)

   y_pred    = svm.predict(X_test)

   svm_acc = accuracy_score(y_pred, y_test)
   svm_prec = precision_score(y_pred, y_test,average='weighted')
   svm_rec = recall_score(y_pred, y_test,average='weighted')
   svm_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
]: storeResults('SVM',svm_acc,svm_prec,svm_rec,svm_f1)
```

Fig 6 SVM

Gradient Boosting Decision Tree (GBDT), builds an ensemble of decision trees sequentially, correcting errors in each iteration. Its ability to capture intricate patterns and interactions within healthcare data makes GBDT a valuable choice. By combining weak learners into a robust model, GBDT enhances predictive accuracy, making it suitable for this project where nuanced relationships in medical data are crucial for effective classification and decision-making.

```
from sklearn.ensemble import GradientBoostingClassifier
clf1 = DecisionTreeClassifier()
clf2 = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0,max_depth=1, random_state=0)

eclf1 = VotingClassifier(estimators=[('ad', clf1), ('rf', clf2)], voting='soft')
eclf1.fit(X_train,y_train)
y_pred    = eclf1.predict(X_test)
gbdt_acc = accuracy_score(y_pred, y_test)
gbdt_prec = precision_score(y_pred, y_test,average='weighted')
gbdt_rec = recall_score(y_pred, y_test,average='weighted')
gbdt_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('DT - GR',gbdt_acc,gbdt_prec,gbdt_rec,gbdt_f1)
```

Fig 7 GBDT

Naive Bayes, is a probabilistic classifier based on Bayes' theorem. Despite its simplistic assumptions, it performs well in healthcare data classification by assuming independence between features. Its efficiency in processing large datasets and quick training make Naive Bayes suitable for this project, contributing to the diverse set of algorithms employed for optimal medical data classification in Emergency Departments.

Naive Bayes

```
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()

nb.fit(X_train, y_train)

y_pred    = nb.predict(X_test)

nb_acc = accuracy_score(y_pred, y_test)
nb_prec = precision_score(y_pred, y_test,average='weighted')
nb_rec = recall_score(y_pred, y_test,average='weighted')
nb_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('Naive Bayes',nb_acc,nb_prec,nb_rec,nb_f1)
```

Fig 8 Naïve bayes

Voting Classifier with Naive Bayes and Logistic Regression (VNBLR), combines the strengths of Naive Bayes and Logistic Regression through a voting mechanism. It leverages the diverse learning strategies of both algorithms to enhance overall predictive performance. VNBLR's ability to handle different facets of healthcare data, combining probabilistic and regression-based approaches, makes it a valuable component in the ensemble. The complementary nature of Naive Bayes and Logistic Regression contributes to VNBLR's effectiveness in medical data classification within Emergency Departments.

```
from sklearn.ensemble import VotingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
clf1 = GaussianNB()
clf2 = LogisticRegression()

eclf1 = VotingClassifier(estimators=[('ad', clf1), ('rf', clf2)], voting='soft')
eclf1.fit(X_train,y_train)
y_pred    = eclf1.predict(X_test)
vnblr_acc = accuracy_score(y_pred, y_test)
vnblr_prec = precision_score(y_pred, y_test,average='weighted')
vnblr_rec = recall_score(y_pred, y_test,average='weighted')
vnblr_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('VNBLR',vnblr_acc,vnblr_prec,vnblr_rec,vnblr_f1)
```

Fig 9 Voting classifier

4. EXPERIMENTAL RESULTS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

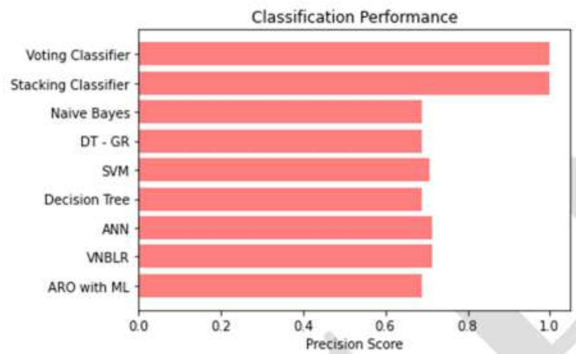

Fig 10 Precision comparison graph

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

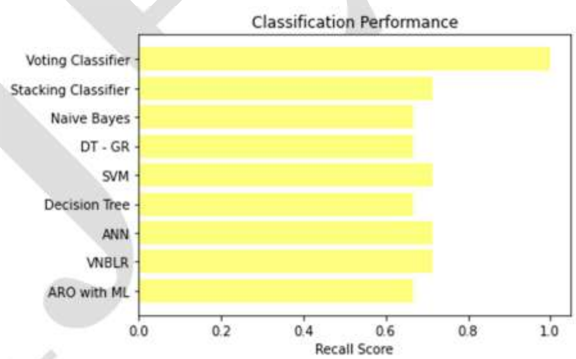

Fig 11 Recall comparison graph

Accuracy: Accuracy is the proportion of correct predictions in a classification task, measuring the overall correctness of a model's predictions.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

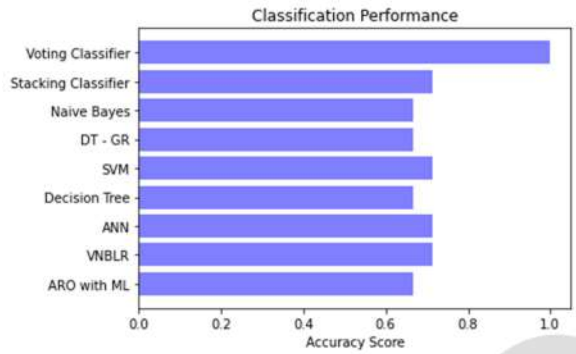

Fig 12 Accuracy graph

F1 Score: The F1 Score is the harmonic mean of precision and recall, offering a balanced measure that considers both false positives and false negatives, making it suitable for imbalanced datasets.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$

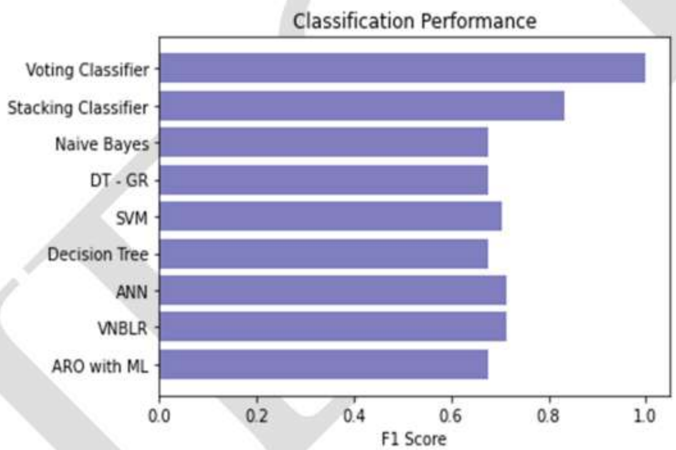

Fig 13 F1Score

	ML Model	Accuracy	Precision	Recall	F1_score
1	VNBLR	0.714	0.714	0.714	0.714
2	ANN	0.714	0.714	0.714	0.714
3	Decision Tree	0.667	0.689	0.667	0.676
4	SVM	0.714	0.708	0.714	0.704
5	DT - GR	0.667	0.689	0.667	0.676
6	Naive Bayes	0.667	0.689	0.667	0.676
7	**Extension- Stacking Classifier**	**0.714**	**1.000**	**0.714**	**0.833**
8	**Extension- Voting Classifier**	**1.000**	**1.000**	**1.000**	**1.000**

Fig 14 Performance Evaluation

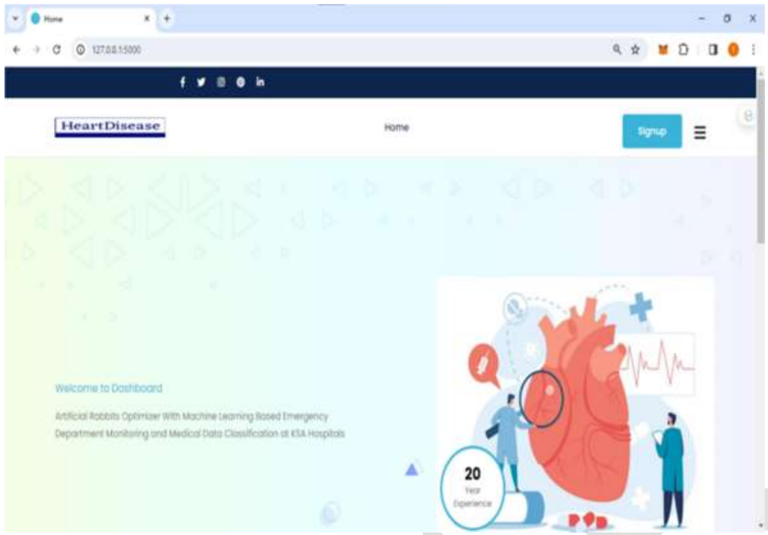

Fig 15 Home page

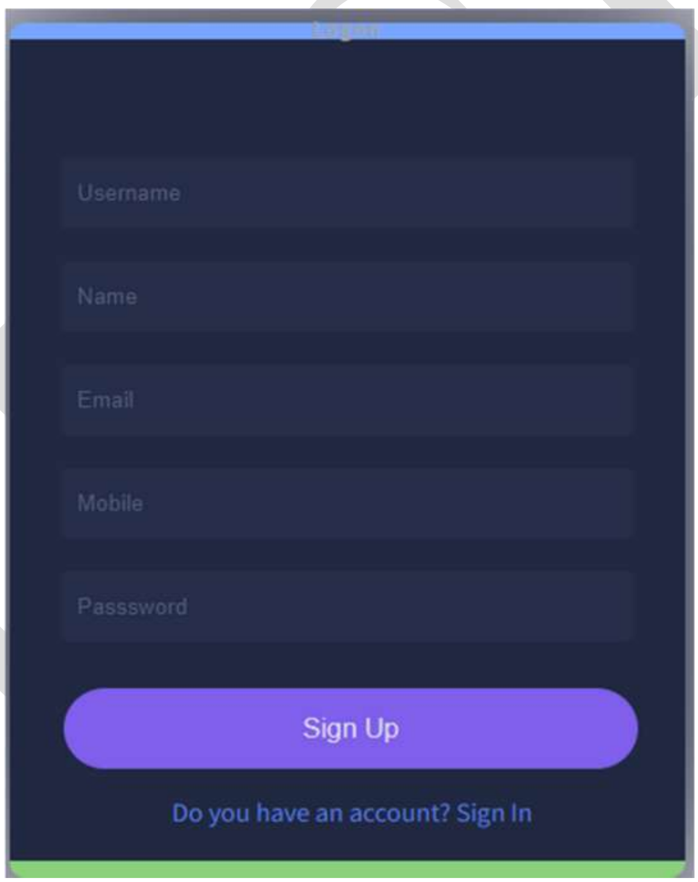

Fig 16 Signin page

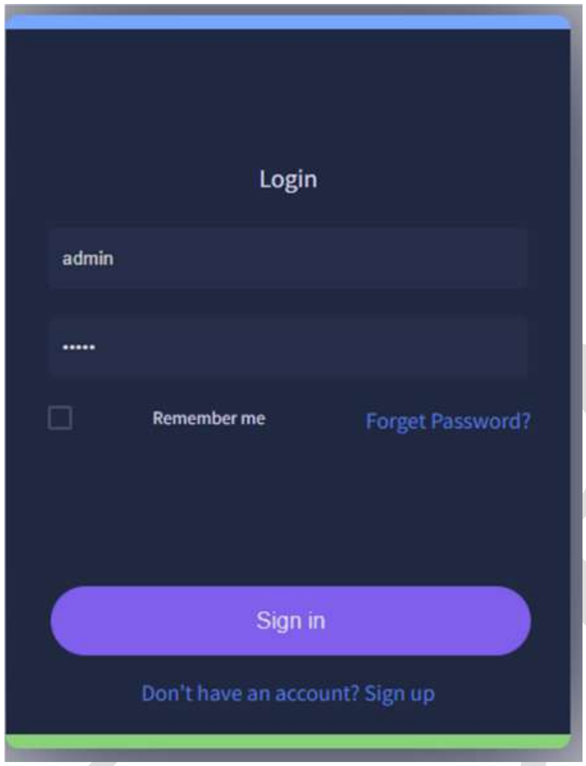

Fig 17 Login page

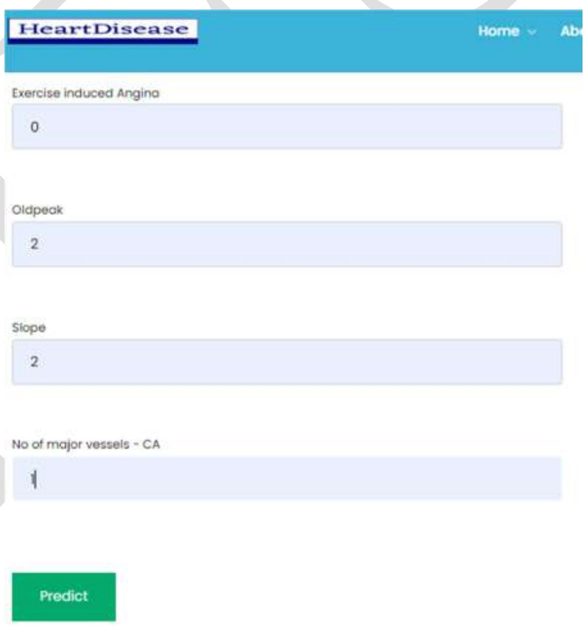

Fig 18 User input

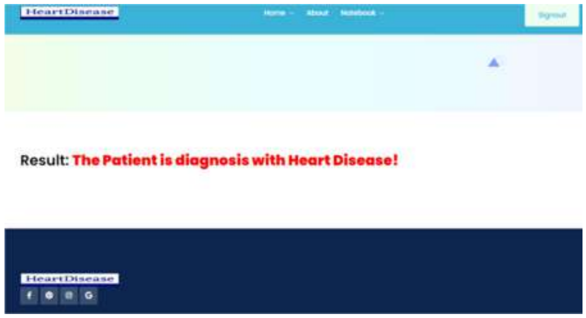

Fig 19 Predict result for given input

5. CONCLUSION

The integration of diverse machine learning algorithms, including Decision Tree, Support Vector Machine, Neural Network, GBDT, Naive Bayes, and VNBLR, in the proposed system establishes a robust foundation for accurate medical data classification in Emergency Departments. The application of the Artificial Rabbit Optimizer (ARO) for feature engineering enhances the system's adaptability to nuanced healthcare data, optimizing the selection of relevant features and improving overall model performance. The ensemble approach, combining multiple classifiers through Stacking and Voting techniques as extension to the project, demonstrates the project's commitment to leveraging the strengths of individual algorithms, resulting in enhanced predictive accuracy for diverse medical scenarios. The incorporation of Flask and SQLite facilitates a user-friendly interface, making the model accessible to a broader audience. The front-end design allows for user testing, input validation, and seamless model predictions, enhancing practical usability. The project's success lies in its potential to revolutionize healthcare monitoring in Emergency Departments, offering a scalable and adaptable solution that aligns with the evolving needs of medical practitioners, ultimately contributing to improved patient care and outcomes.

6. FUTURE SCOPE

Future enhancements could involve researching and integrating state-of-the-art machine learning algorithms to elevate predictive accuracy, ensuring the system remains at the forefront of medical data classification technology. A potential avenue for expansion is the incorporation of real-time data streams and continuous monitoring, enabling timely interventions and enhancing the system's responsiveness in Emergency Departments. Collaboration with medical professionals, researchers, and technology experts is essential for refining the system based on evolving healthcare needs and incorporating domain-specific insights for optimal performance. Exploring opportunities for the global application of the system involves adapting it to diverse healthcare settings worldwide and addressing specific regional healthcare challenges to ensure widespread utility. Future development could focus on implementing robust security protocols to safeguard sensitive medical data, ensuring compliance with evolving data protection regulations, and fostering trust in the system's reliability.

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