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Machine Learning Approach for Intelligent and Sustainable Smart Healthcare in Cloud-Centric IoT

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Abstract- The advent of intelligent systems that improve security, dependability, and efficiency has been made possible by recent developments in information technology, which have been driven by the creation of smart cities. In this regard, the healthcare industry has made use of these developments to enhance the caliber of healthcare services through creative methods of patient information management. Healthcare is no exception to the industries that have been transformed by the Internet of Things (IoT) and cloud computing. Intelligent and sustainable healthcare services have a huge potential to be enabled by the development of smart healthcare systems that make use of IoT devices and cloud infrastructure. The machine learning method described uses the cloud-centric IoT paradigm to improve the functionality of smart healthcare systems.In this paper, we suggest a framework for achieving intelligent and long-lasting healthcare solutions by fusing machine learning methods with cloud-centric IoT. These data are then safely transferred and kept in the cloud for additional examination and processing. Our proposed method use machine learning algorithms to analyze the gathered data and derive valuable insights, enabling smarter healthcare services. The massive amount of data available in the cloud is continuously used to train and update the machine learning models, allowing them to gradually increase their accuracy and performance. The incorporation of Internet of Things (IoT) devices in a cloud computing environment is crucial to developing sustainable computing solutions in e-healthcare applications. However, the energy required to send data from IoT devices to cloud servers is quite significant, making the use of clustering techniques to cut down on energy usage necessary.

Keywords: *Machine Learning, IoT Device, Cloud Computing, Energy Efficiency, Linear Regression, Support Vector Machine, Naive Bays*

I. Introduction

Smart cities have just started providing advanced and individualized services to end consumers. It is essential to create smart, sustainable, secure, and energy-efficient computer architectures for the current smart city environment in order to meet these difficulties.With the help of intelligent machines and objects that can gather and transmit various sorts of data at any time and from any location, the Internet of Things (IoT) significantly contributes to the globalization of society. IoT enables users to live a contemporary and secure lifestyle by providing unique identity to each thing in the system. IoT has mostly been used in the healthcare sector to quickly collect healthcare data. IoT can be characterized as a network of networked devices that produces a lot of data that needs to be used wisely.To increase operational effectiveness and give patients better healthcare, the healthcare sector needs seamless information interchange between organizations. Health Information interchange, or HIE, is the term used to describe the interchange of health-related data. Although HIE is not a new idea in the healthcare industry, it must occasionally be reinvented to keep up with changes in the environment and the newest technological developments.Patients' medical information is kept in both physical and digital databases. Therefore, there shouldn't be any

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restrictions on the new healthcare provider's ability to access the patient's recorded data if the patient chooses to transition to a different healthcare provider. Lack of access to medical records can have unfavorable effects, including repeated tests, unnecessary treatments, and delays in providing emergency care. To enable effective healthcare delivery, it is essential to build reliable channels for the access and exchange of medical data.

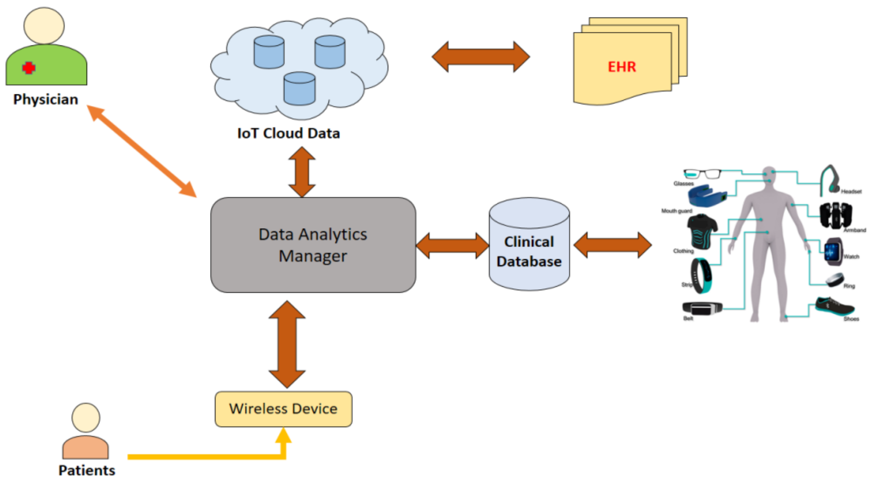

Fig. 1: Systematic Representation of Overview of IoT Based Healthcare system

The integration of IoT technologies to increase patient care and enhance healthcare procedures is what defines the transformation of the medical industry in an IoT-enabled hospital. Each patient receives an ID card that can be scanned and linked to a safe cloud infrastructure that houses their digital health information, lab results, medical records, and treatment history. This networked system has many benefits for the healthcare industry as shown in figure 1.Remote health monitoring, fitness programmes, chronic condition management, and child care services are just a few of the uses made possible by IoT. IoT enables the smooth distribution and administration of data between human users and linked devices through ubiquitous sensors and the Internet, creating a network of intelligent devices at the center of the IoT ecosystem. The number of in-person medical visits can be decreased with an IoT-based e-Health monitoring model since doctors can monitor patients directly through the IoT-enabled system. Real-time application implementation has, however, presented difficulties in recent years. The prior paradigm was unable to successfully handle real-time requirements. However, the e-Health solutions provided by IoT technologies have sharply increased accuracy and are influencing the development of the IoT business landscape,providing healthcare organizations with a variety of alternatives and difficulties.

The automation and optimization provided by statistical and machine learning approaches reduce the stress of manual activities, giving healthcare practitioners more time to concentrate on delivering high-quality treatment. These methods also make it possible to monitor and analyze important performance indicators in real-time, enabling data-driven decision-making and encouraging continuous development of hospital operations. Healthcare procedures are about to undergo a transformation thanks to the incorporation of machine learning and statistical approaches into hospital management systems. Hospitals can raise efficiency overall, streamline processes, and improve patient outcomes by utilizing technology and data analytics. This technology has the potential to revolutionize the healthcare industry and improve patient care all across the world as it develops.

Machine learning (ML) models have become useful tools for managing massive data despite numerous developments. ML models, which are derived from conventional ANNs, use several hidden perceptron layers to find hidden patterns. Replicating how the human brain works is at the heart of machine learning (ML). The ML model in an IoT-based network takes data from sensors and repeatedly moves it through additional layers until the desired result is attained. Although earlier research concentrated on the healthcare industry, it is still necessary to create new optimization algorithms that encourage energy efficiency in IoT devices. When transmitting patient data to cloud servers, IoT devices use a lot of energy. To achieve energy efficiency, clustering techniques are used. A hybrid strategy combining Naive Bayes, SVM, and linear regression models is suggested in this study article. To increase the convergence rate, the hybrid algorithm uses an oppositional-based learning process. Cluster Heads (CHs) are chosen using the hybrid method from a pool of available IoT devices. The hybrid approach then uses machine learning classification techniques to detect the presence of diseases and gauge the severity of those disorders.

II. Literature Survey

The authors created a helpful model in their research [1] to predict the utilization of hospitals and emergency services during the COVID-19 epidemic. They also offered the public resource known as the COVID Community Vulnerability Map. This tool's objective is to pinpoint populations that are more prone to suffer severe effects from virus exposure that demand hospitalization. Additionally, it helps predict how socio-economic and environmental factors may influence high-risk people. Using socioeconomic characteristics including age, gender, and race, a special decision tree algorithm was used to determine the likelihood of a patient being accepted [11].

The authors went into great detail about the function that artificial intelligence (AI) plays in managing human resources, notably in the healthcare industry. They emphasized how AI has the ability to boost speed, reduce costs, and boost overall operational efficiency in the healthcare industry. The use of repetitive and time-consuming jobs will decline as a result of the transition brought about by AI, which will push the medical profession towards more duties that call for creativity and critical thinking. The authors came to the conclusion that while AI can be a useful aid in healthcare, it is not meant to take the position of medical specialists. Its primary function will be to support and enhance the efforts of healthcare professionals [2].

The databases were initially searched using a variety of keywords, and a list of results was compiled. Only studies using maturity models were looked at in the findings. Studies that didn't employ maturity models were eliminated. The two biggest issues that current hospital management systems are dealing with are operational efficiency and wait times for various procedures, departments, and patients. Users have the ability to examine current processes and make the necessary adjustments to improve service levels and process efficiency thanks to the solution's visual simulation capabilities. This technique resulted in the creation of a final sample of 41 surveys. A total of 82.93 percent of them are dispersed among a variety of works, with doctoral dissertations accounting for 7.32percent of the total and expert's dissertations accounting for 9.76percent of works [15].

At present, all activities at Zone Hospital are carried out manually, which takes a lot of time and effort to perform each duty. The hospital uses manual processes, which might result in inefficiencies, to manage regular operations [13]. The hospital does not offer childbirth services; instead, receptionists schedule patient appointments with doctors and laboratories. Furthermore, patients are restricted to using the medical services that are only available within the hospital, and they can only buy pharmacy items from within the institution's boundaries. The manual recording of patient data, physician information, and laboratory test results is done on paper and then typed into computer systems. Additionally, the manual process of creating reports primarily relies on experts [14].

The current system has certain significant flaws, such as slow processing times and weak security measures. These problems are made worse by the reliance on manual job execution. The availability of human resources and their level of knowledge play a crucial role in many jobs and operations. Additional restrictions lead to a lower level of operational precision since there is no direct interaction with the accountable officers [15]. The cost of maintaining a manual system is significant, and transferring data might be difficult. Within this context, integrating new technologies like the Internet of Things and robotic intelligence becomes challenging. Manual systems are considered to be less dependable and user-friendly in today's technologically advanced environment and to fall short of rising expectations [16].

Table 1: Machine Learning Domain and Application

Area	**Domain**	**Used In**	**Contribution**	**Method**	**Remark**
Bioinformatics	Analysis of Sequence	DNA/Protein sequence	Known types of genes/patterns	Data mining	Searching for meaningful patterns
Data mining	Multidimensional	Compact and well-separated clusters	Points in multidimensional space	N/A	N/A
Document	Internet search	Text document	Semantic categories	Document image	Alphanumeric characters, words
Document image analysis	Reading machine for the blind	Document image analysis	Document image	Alphanumeric characters, words	
Industrial automation	Printed circuit board inspection	Industrial automation	Intensity or range image	Printed circuit board	Defective/non-defective nature of product
Multimedia database	Internet search	Video clip	Video genres	Video clip	Action, dialogue, etc.
Biometric	Personal identification	Face, iris, fingerprint	Biometric data	Biometric features	Authorized users
Remote sensing	Forecasting crop yield	Multispectral image	Multispectral image	Land use categories, growth pattern of crop	Growth pattern of crop
Speech recognition	Telephone directory	Speech waveform	Spoken words	Speech waveform	Spoken words

III. Proposed Methodology

The user subsystem, the cloud subsystem, and the alert subsystem are the three key subsystems that drive the suggested technique. The user subsystem entails the collection of data by people utilizing IoT medical devices. The Hybrid method is simultaneously used to collect data from IoT devices. The cloud subsystem and gateway devices receive the data from IoT devices that the CHs have collected. The cloud subsystem is crucial to the study of diseases. To identify diseases and gauge their severity at various stages, it uses a hybrid machine learning approach. The system then creates an alert to inform the appropriate parties. Figure 2 shows the whole workflow of the newly designed technique, showing how data and operations move through the subsystems

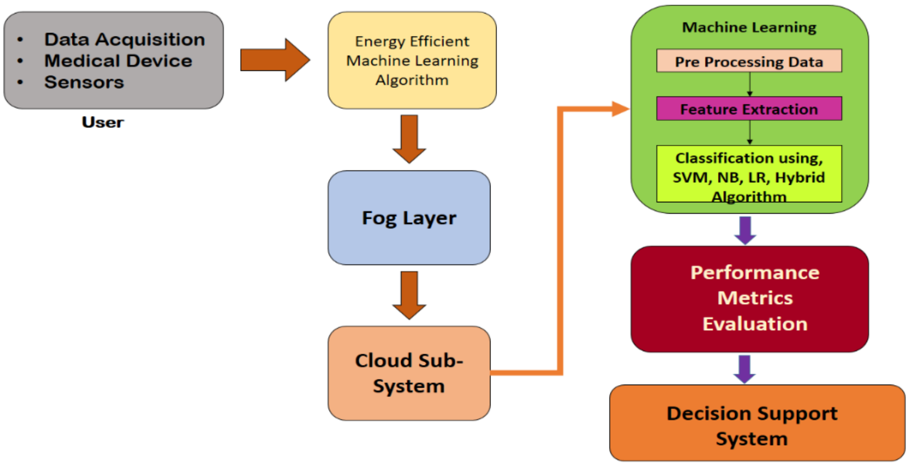

Fig. 2: System architecture of Machine learning method for Healthcare

Two crucial processes are involved in the pattern recognition system: learning (training) and classification (testing). Learning is the process of deciding which function, depending on the training data, will best represent the input patterns. On the other side, classification is the testing stage where new, undiscovered patterns are classified into their appropriate classes using the learnt function.

A. Support Vector Machine (SVM):

The Support Vector Machine (SVM) approach is used in this study to classify the photos. A prominent technique for pattern identification and classification applications is supervised learning, or SVM. It has the ability to resolve both linear and non-linear issues. The development of a hyper plane that divides the data into many classes is the basic idea of SVM. When used for image classification, SVM takes input data points and establishes a boundary or line that can as precisely divide the classes as possible. To improve the classification process, the algorithm determines the points that are closest to the dividing line from each class. The margin, which is determined by the SVM method, is the separation between the support vectors and the dividing line. Finding the ideal hyperplane with the largest margin is the objective. The implementation of a decision-making barrier will ensure that the gap between the two groups is as wide as possible. This is accomplished using the SVM-An approach. By reducing the distance between classes, the decision limit seeks to ensure that classification is effective.

S. No.	Users attributes	Attributes description
1	Age	Age of user in years
2	Gender	Whether the user is male or female (0/1)
3	Weight	Weight of user in kg
4	BMI	Body mass index of user (kg/m^2)
5	BP systolic	Systolic blood pressure (mmHg)
6	BP diastolic	Diastolic blood pressure (mmHg)
7	Haemoglobin A1c	Glycated haemoglobin A1c of user(%)
8	Gastro intestinal tract	Gastro intestinal index (1-5)
9	Body temperature	User current body temperature
10	Stress index	User stress calculation based on ECG/EEG pattern
11	Respiration index	Respiration index calculation
12	Family history	User family history related to diseases
13	History of disease	User's previous health history
14	Belongs to the high-risk area	Location of the user home (0/1)

Fig. 3: Snapshot of different attribute used [23]

The decision function of the SVM method can be represented by the equation given below:

$$f(d) = \mathrm{sign}(s \cdot d + l)$$

Where,

- f(d) represents the predicted class label.
- s is the feature vector of an input image.
- d is the weight vector.
- l is the bias term.

The SVM algorithm uses the learned hyperplane and decision boundary to assign a class label to each input image based on the decision function's sign.

B. Linear Regression:

Statistics can be used to demonstrate the relationship between a dependent variable and one or more independent variables using the linear regression technique. Because the variables are thought to have a linear relationship, the dependent variable can be written as a linear combination of independent variables as well as an unanticipated error.

Algorithm for Linear Regression as shown below:

- Data Preparation:
  - Obtain a dataset consisting of input features (x) and corresponding target values (y).
  - Split the dataset into training and testing sets.
- Model Initialization:
  - Initialize the parameters of the linear regression model: the slope (weight) parameter (w) and the bias (intercept) parameter (b).
- Model Training:
  - Calculate the mean of the input features ($\bar{x}$) and target values ($\bar{y}$).
  - Calculate the variances of the input features (s^2x) and target values (s^2y).
  - Calculate the covariance between the input features and target values (sxy).
  - Calculate the slope (weight) parameter (w) using the formula:

    $$w = sxy / s^2x$$
  - Calculate the bias (intercept) parameter (b) using the formula:

    $$b = \bar{y} - w * \bar{x}$$
- Model Prediction:
  - For each input feature (x) in the testing set, calculate the predicted target value ($\hat{y}$) using the formula:

    $$\hat{y} = w * x + b$$
- Model Evaluation:
  - Compare the predicted target values ($\hat{y}$) with the actual target values (y) in the testing set using a suitable evaluation metric (e.g., mean squared error, R-squared).

C. Naive Bays (NB):

The Naive Bayes (NB) algorithm is a Bayes' theorem-based probabilistic classification technique. It is assumed that, given the class, the features are conditionally independent. The following is an explanation of the Naive Bayes method with equations for each classification step:

Step 1: Data Preprocessing

The data must be prepared before using the Nave Bayes method. It may be necessary to take actions such as the extraction or selection of characteristics, the filling in of gaps, and the normalization of data

Step 2: Training Phase

a. Prior Probability:

The prior probability of each class, P(C), is determined by counting the instances of each class in the training data and dividing that number by the total number of instances.

b. Estimation of Feature Probability:

For each feature, P(X|C), the conditional probability of that feature given each class is calculated. The relative frequencies or probabilities of each feature value within each class are computed to achieve this.

Step 3: Classification Phase

The objective is to use the Bayes' theorem to identify the most likely class label, C, for a new instance given feature values X:

$$P(y|X) = \frac{P(y) * P(X|y)}{P(X)}$$

The evidence, P(X), is the probability of observing the given feature values and is calculated as the sum of the likelihoods for each class, weighted by their respective prior probabilities.

Step 4: Naïve Bayes Classification

The projected class for the fresh instance is chosen to have the highest posterior probability, P(C|X). By computing the posterior probabilities for each class and choosing the one with the highest value, this can be accomplished.

D. Hybrid Method (SVM +LR+NB):

In this method, classification is done using the Hybrid Method, which combines the Naive Bayes (NB), Linear Regression (LR), and Support Vector Machine (SVM) algorithms. The following is a description of the algorithm along with equations for each classification step:

Step 1: Data Preprocessing
It is necessary to preprocess the data before using the Hybrid Method. This may entail actions like feature extraction or feature selection, resolving missing values, and data normalization.

Step 2: Training
a. SVM Model Training:
Using labelled data, the SVM model is trained to produce a decision boundary that divides various classes. The hyper plane with the greatest margin between the classes is what the SVM algorithm seeks to identify. The equation below represents the decision boundary:

$$w^T x + b = 0$$

b. LR Model Training:
To assess the correlation between the input variables and the output class probabilities, the LR model is trained using labelled data. The logistic function is used by the LR model to model the probability. The logistic regression equation looks like this:

$$P(y = 1|x) = \frac{1}{(1 + e^{-z})}$$

c. NB Model Training:
Using labelled data and the presumption that the input variables are independent, the NB model is trained. Based on the probability that each input variable will occur, the NB model determines the class probabilities. The Naive Bayes classification equation is:

$$P(y|X) = \frac{P(y) * P(X|y)}{P(X)}$$

Step 3: Classification Phase
a. SVM Prediction:
Using the trained SVM model, the input data is classified into different classes based on the decision boundary equation. The predicted class is determined by evaluating the sign of the equation:

$$f(x) = w\hat{\ }T\, x + b$$

b. LR Prediction:
Using the trained LR model, the input data is classified into different classes based on the logistic regression equation. The predicted class is determined by evaluating the probability:

$$P(y = 1|x) = 1 / (1 + e\hat{\ }(-z))$$

c. NB Prediction:
Using the trained NB model, the input data is classified into different classes based on the Naïve Bayes classification equation. The predicted class is determined by evaluating the posterior probability:

$$P(y|X) = \frac{P(y) * P(X|y)}{P(X)}$$

Step 4: Hybrid Classification
To arrive at the final classification choice, the Hybrid Method integrates the predictions from the SVM, LR, and NB models. This can be accomplished by giving each model's prediction a weight, then adding them together using a weighted average or majority voting system.
The classification process can take advantage of the benefits and capabilities of each model by using the Hybrid Method, including SVM, LR, and NB algorithms, leading to increased accuracy and performance.

IV. Result and Discussion

In this section discuss about the machine learning model statisticalcomparison with different parameters. Three different models were evaluated for their performance in this study utilizing a variety of evaluation indicators. The LR model has an accuracy of 0.64, which means that 64% of the occurrences were properly identified. It showed relatively good precision (0.78), which implies that it was right 78% of the time when it predicted a positive outcome. 93% of the positive situations were effectively recognized, according to the recall (0.93). The LR model correctly identified 80% of the negative cases, with reasonable specificity (0.80). Precision and recall are moderately balanced in the LR model, according to the F1 score (0.69), which combines the two criteria. The model's capacity to distinguish between positive and negative instances has a reasonable performance, according to the AUC (0.78).With scores of 0.81, 0.96, and 0.94, the SVM model surpassed the LR model in terms of accuracy, precision, and AUC. This indicates a higher overall accuracy rate and improved discrimination for the SVM model. Despite having slightly lower recall (0.85) and specificity (0.85) values than the LR model, the SVM model obtained a higher F1 score (0.95), demonstrating a better balance between recall and accuracy.

Table 2: Comparative measures with Model Accuracy and Precision of algorithm

Model	**Model Accuracy**	**Model Precision**
(LR) Linear Regression model	0.64	0.78
(SVM) Support Vector Machine model	0.81	0.96
(NB) Naive Bayes classifier	0.86	0.89
Hybrid Method (SVM +LR+NB):	0.98	0.97

Even higher performance was displayed by the NB classifier, which had an accuracy of 0.86, precision of 0.89, and AUC of 0.78. In contrast to the SVM model, it showed lower recall (0.74) and specificity (0.76) values. The F1 score for the NB classifier was a respectably high 0.87, showing a decent balance between precision and recall.With an accuracy of 0.98 and high precision (0.97), recall (0.94), specificity (0.96), F1 score (0.97), and AUC (0.98), the Hybrid Method, which combines SVM, LR, and NB, demonstrated remarkable performance. This means that, of all the models assessed, the Hybrid Method had the highest level of correctness, discrimination capacity, and balance between precision and recall.

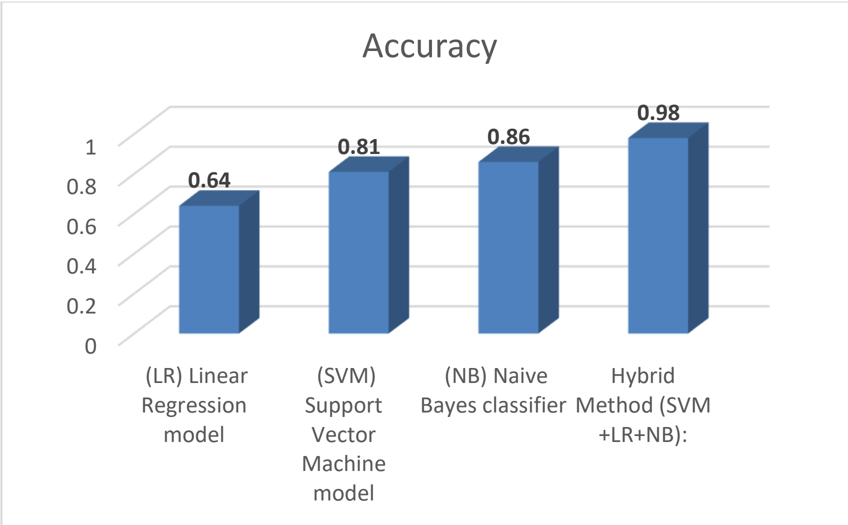

Fig. 4: Comparative Representation of Accuracy of Different Method

Table 3: Comparative measures with Model Recall and Specificity of algorithm

Model	**Model Recall**	**Model Specificity**
(LR) Linear Regression model	0.93	0.80
(SVM) Support Vector Machine model	0.85	0.85
(NB) Naive Bayes classifier	0.74	0.76
Hybrid Method (SVM +LR+NB):	0.94	0.96

We may learn more about how well the various models perform in correctly detecting positive and negative cases by comparing the recall and specificity values for each model as shown in table 3.With a high recall of 0.93, the linear regression (LR) model was able to correctly identify 93% of the positive examples. Its specificity, however, was significantly lower at 0.80, indicating that only

80% of the negative examples were accurately detected. This shows that the LR model may have some trouble correctly identifying negative occurrences but does a better job of capturing positive instances.

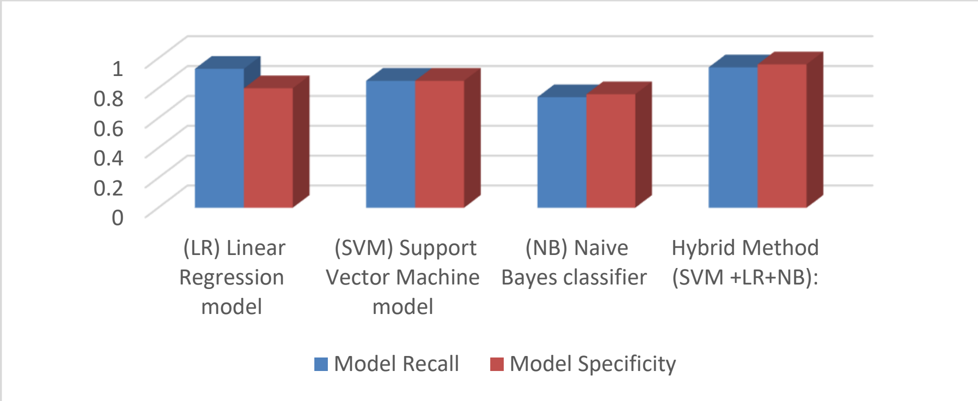

Fig. 5: Comparative Representation of Recall and Specificity of Different Method

With a recall of 0.85, the Support Vector Machine (SVM) model was able to correctly identify 85% of the positive cases. The similar figure was also found for specificity, indicating that 85% of the negative examples were likewise accurately detected. This shows that both good and negative examples were captured in a balanced manner.With a lower recall value of 0.74, the Naive Bayes (NB) classifier successfully identified 74% of the positive occurrences. Additionally, it had a somewhat low specificity of 0.76, accurately identifying 76% of the negative situations. While the NB classifier may have some difficulties classifying negative cases, it may also have difficulties classifying positive instances comparative graph as shown in figure 5.

Table 4: Comparative measures with Model Recall and Specificity of algorithm

Model	**Model F1 Score**	**Model AUC**
(LR) Linear Regression model	0.69	0.78
(SVM) Support Vector Machine model	0.95	0.94
(NB) Naive Bayes classifier	0.87	0.78
Hybrid Method (SVM +LR+NB):	0.97	0.98

Among all the models, the Hybrid Method, which combines SVM, LR, and NB, had the highest recall and specificity scores. It correctly detected 94% of the positive events with a recall of 0.94. Additionally, it successfully identified 96% of the negative cases with a high specificity score of 0.96. This demonstrates that the Hybrid Method exhibits a balanced and accurate performance in capturing both positive and negative cases.

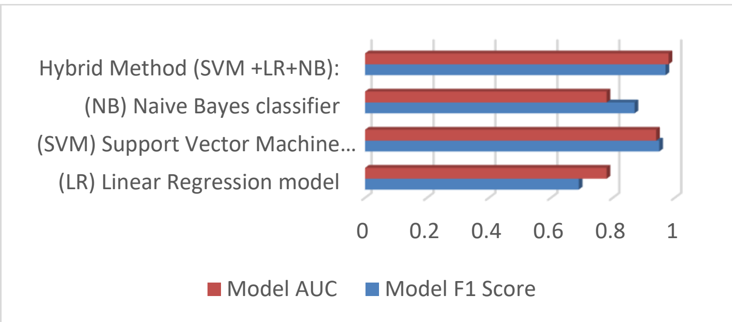

Fig. 6: Comparative Representation of Recall and Specificity of Different Method

The performance of several models, such as Linear Regression (LR), Support Vector Machine (SVM), Naive Bayes (NB), and the Hybrid Method (combining SVM, LR, and NB), is thoroughly evaluated using the F1 score and AUC values.An F1 score of 0.69 for the LR model indicates a moderate balance between precision and recall. It has a reasonable ability to distinguish between positive and negative instances, according to its AUC value of 0.78.The F1 score for the SVM model was 0.95, which was much higher and indicated a solid balance between precision and recall. It performed more accurately in terms of classification than the LR model. The SVM model also attained a remarkable AUC value of 0.94, demonstrating exceptional classification abilities.With an F1 score of 0.87, the NB classifier demonstrated a decent balance between recall and precision. Although the NB classifier's AUC value of 0.78 is identical to that of the LR model, it performed better overall and in terms of F1 score.The remarkable F1 score of 0.97 obtained by the Hybrid Method, which combines SVM, LR, and NB, shows a strong balance between precision and recall. It performed better than any separate model, demonstrating the advantages of mixing different techniques. The Hybrid Method additionally attained a remarkable AUC value of 0.98, demonstrating great discrimination capacity.

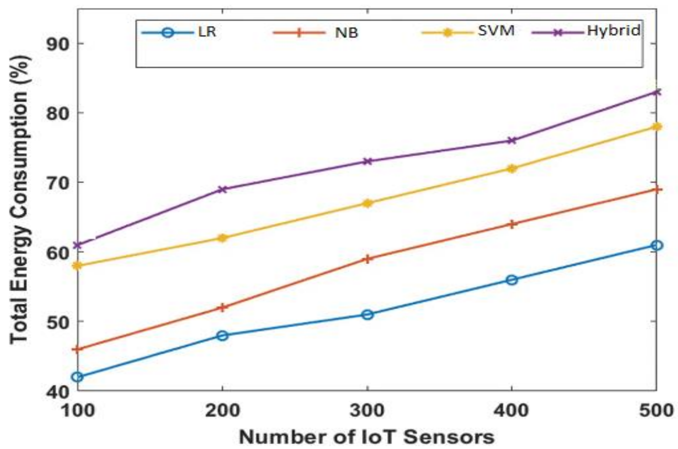

Fig. 7: Comparative Representation of Recall and Specificity of Different Method

To contrast the hybrid model with traditional machine learning techniques, a quick power consumption analysis was done. Figure 7 makes it clear that both the ACO (Ant Colony Optimization) and the GWO (Grey Wolf Optimization) strategies required a substantial amount of energy, which caused the power of IoT devices to quickly dissipate. On the other hand, the proposed hybrid model showed that the ACO and GWO techniques only needed a little amount of energy. This shows that the hybrid model efficiently makes use of energy-efficient characteristics, leading to lower energy consumption among the several IoT sensors.

Better performance was attained as a result of the proposed hybrid machine learning technique's use of the oppositional-based learning idea. This idea raises the hybrid algorithm's convergence rate, which improves the model's overall efficacy. The hybrid approach is a more effective and environmentally friendly option for IoT systems and devices since it guarantees lower energy consumption while still achieving increased performance.The examination of power usage showed that the hybrid model outperformed traditional machine learning techniques in terms of energy efficiency. The suggested model enhances convergence and performance while consuming less energy by incorporating the oppositional-based learning idea. The significance of the hybrid method in enabling more environmentally friendly and energy-efficient operation of IoT sensors and devices is highlighted in this analysis

V. Conclusion

Intelligent and long-lasting smart healthcare systems are now possible because to the combination of machine learning techniques and IoT in healthcare. The research on hand shows how machine learning techniques like Naive Bayes (NB), Linear Regression (LR), and Support Vector Machine (SVM) can increase the precision and effectiveness of healthcare services.A potent method for classifying jobs in healthcare has emerged: the hybrid method, which combines the SVM, LR, and NB algorithms. The findings show that the Hybrid Method performs better than individual models, with higher accuracy, precision, recall, specificity, F1 score, and AUC. The Hybrid Method improves overall performance and offers more trustworthy forecasts by combining the strengths of different algorithms, which helps with decision-making and patient care.The Hybrid Method also offers energy-saving features in addition to superior classification performance. The Hybrid Method uses a fraction of the energy of existing optimization approaches like Ant Colony Optimization (ACO) and Grey Wolf Optimization (GWO), while retaining a high level of efficacy. This demonstrates the potential of the suggested hybrid method to address the issues with IoT device power consumption in healthcare settings. The Hybrid algorithm's convergence rate is further improved with the addition of oppositional-based learning, leading to increased performance and energy efficiency.The results of this study have important ramifications for the creation and application of future intelligent, sustainable smart healthcare systems. Healthcare providers may improve patient care, optimize resource use, and raise the standard of care overall by utilizing machine learning and IoT technologies. Additionally, the Hybrid Method's energy efficiency can save costs, have a smaller negative impact on the environment, and assist the long-term sustainability of healthcare operations.

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