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Next-Gen EHR: Advancing Healthcare with Integrated Recommendations and Decision Support

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Abstract: *The study outlines a holistic strategy for modernizing healthcare administration through the fusion of electronic health records (EHR) and machine learning techniques, including Support Vector Machines (SVM) and Naive Bayes. It addresses challenges in manual patient record management, particularly in countries like India, by proposing an EHR system implementation. The developed web application combines frontend and backend development technologies to streamline record management, enhance data accuracy, and improve healthcare delivery. Additionally, leveraging Naive Bayes and SVM algorithms, the system prioritizes multimedia efficiency and offers health recommendation by analyzing unstructured EHRs. This research contributes to advancing predictive healthcare analytics by exploring the integration of EHRs and machine learning for health recommendation, aiming to enhance patient outcomes and healthcare quality. The findings of this underscore the strength of machine learning in revolutionizing health recommendation and personalized healthcare, thereby paving the way for improved patient care and management.*

Keywords: *EHR, Health recommendation, Prediction, Naive Bayes, SVM*

1. INTRODUCTION

Over the past few years, there has been a notable transformation in the healthcare sector driven by technological progress, especially in electronic health records (EHR) and machine learning. This research paper delves into the integration of EHR systems with machine learning algorithms to the health recommendation based on comprehensive patient health data. The introduction of EHR systems has fundamentally changed how patient information is stored and managed, providing healthcare providers with a digital archive containing a patient's entire medical background[1].

However, the current manual method of managing and storing patient records in hospitals in countries like India is time-consuming, error-prone, and inefficient, leading to incomplete or inconsistent information, data loss, and discrepancies in data across different storage locations. To address these challenges, this study proposes the execution of an EHR system to transform the manual process of managing and retrieving hospital information into an electronic format. By digitizing patient records, the EHR system can ensure real-time access to patient information as they enter and leave the hospital.

The main aim of this study is to create a computerized software solution that can replace the manual process of handling patient records within hospitals. The software will streamline the process of maintaining accurate and up-to-date patient records, reducing the risk of data loss and improving overall healthcare delivery. Additionally, the EHR system will provide a centralized repository for storing and accessing patient information, eliminating the need for multiple copies of data and ensuring data consistency across different departments.

The methodology involves the development of a web application that allows patients to input their entire health records, which will interface with a machine learning model trained based on the symptoms to provide the health recommendation. Naive Bayes and SVM are used as machine learning algorithms for this purpose. Naive Bayes is used for its simplicity, speed, and performance in multi-class prediction tasks, while SVM is used for its effectiveness in high-dimensional spaces and memory efficiency, particularly suitable for complex medical data with many features. This proactive approach to healthcare holds promise for revolutionizing disease prevention and early intervention strategies, thereby enhancing patient outcomes and reducing healthcare costs.

While there are potential advantages, it's crucial to tackle challenges such as privacy concerns surrounding data, issues with data accuracy, and the need for clear interpretation of algorithms to ensure ethical and efficient utilization of predictive models in clinical environments [2]. This research contributes to the discourse on the integration of EHRs and machine learning for disease prediction, advancing the field of predictive healthcare analytics.

2. LITERATURE SURVEY

Electronic Health Records (EHRs) have undergone a remarkable evolution since their inception, starting as brief case reports and gradually evolving into comprehensive patient data systems[3]. The introduction of EHRs in the 1960s represented a significant advancement in healthcare documentation, with the goal of simplifying record-keeping processes and enhancing accessibility to clinical data. By 1992, improvements in hardware had made it more cost-effective, robust, and portable, enabling the utilization of personal computers, local area networks, and the Internet for swift access to medical information [4]. Initially pioneered and utilized in academic medical settings, EHRs have largely transitioned to larger vendor systems. However, many of the initial expectations for EHRs have not been fully realized, and current systems do not entirely meet the demands of the swiftly evolving healthcare landscape. Despite these challenges, since the implementation of the HITECH Act in the United States, which offered financial incentives for healthcare providers to embrace EHR systems, there has been a noticeable uptick in EHR adoption. The healthcare sector stands at the threshold of a transformative shift, with EHR technologies positioned to greatly enhance healthcare practices. Embracing EHR technologies, along with the right software, hardware, and IT infrastructure, can lead to better patient outcomes, increased efficiency, and reduced healthcare costs. While the healthcare sector has been slow to adopt EHR technologies, the American Recovery and Investment Act of 2009 is driving their adoption[5]. Healthcare organizations that fail to adopt EHR technologies risk closure, highlighting the importance of developing effective EHR and IT systems for survival. Both existing and emerging EHR technology are anticipated to set global benchmarks for interoperable applications, facilitating precision medicine and the development of a learning health system.

Electronic Health Records (EHRs) play a pivotal role in enhancing healthcare quality by facilitating the easy sharing of structured medical data among healthcare providers. However, ensuring the privacy and security of patient information is crucial due to its sensitivity. To address security concerns effectively, regulations and standards need to be harmonized. Implementing efficient encryption schemes, Role-Based Access Control (RBAC), and authentication mechanisms like passwords/logins and digital signatures are recommended[6]. Managing EHRs effectively requires a multidisciplinary team to enable the exchange of medical data across different regions. EHRs can significantly improve healthcare quality by enhancing guideline adherence, time efficiency and Adverse Drug Events (ADEs) and reducing medication errors , especially when including Decision Support Systems (DSS)[7]. Proper implementation strategies, such as those outlined by the WHO, are crucial for successful EHR adoption. However, limitations such as heterogeneity and lack of comprehensive data in current studies indicate the need for further research to evaluate different EHR systems and their implementation effectively. EHRs are also valuable tools for assessing healthcare quality and monitoring provider performance, offering automated quality assessment and reducing manual chart review. Despite the potential benefits, a study examining the relationship between patient outcomes and EHR adoption suggests that current EHRs may not yet have a significant impact on patient outcomes, despite being beneficial for billing and compliance measurements[8]. This research utilized observational data obtained from State Inpatient Databases, which were linked to the 2011 American Hospital Association survey. The study concentrated on surgical and medical patients from six large and varied states. Preliminary examination revealed variances in mortality rates, readmissions, and complications among hospitals with complete or partial EHR implementation compared to those lacking EHR systems. However, after adjusting for patient and hospital variables, these variances ceased to exist.

Research in analyzing electronic health record (EHR) data primarily focuses on data sourced from a single institution, utilizing details extracted from clinical notes[9]. Machine learning (ML) techniques have played a crucial role in characterizing various chronic conditions as well as more intricate phenotypes, such as social determinants of health. While supervised deep learning has emerged as the predominant

ML paradigm, semi-supervised and weakly-supervised learning methods have also been employed. Despite the prevalence of ML approaches, the study underscores that they did not consistently surpass rule-based algorithms. However, deep learning generally demonstrated better performance compared to traditional ML techniques. Various research shows potential application of machine learning techniques in identifying health outcomes from EHR data. The paper outlines four scenarios where machine learning can benefit health outcomes based on diagnostic criteria and EHR data format. Scenario 1 involves clear, objective diagnostic criteria based on structured EHR fields; Scenario 2 includes outcomes diagnosed from multiple tests in structured EHR fields; Scenario 3 has clear criteria but in unstructured EHR data; Scenario 4 involves vague criteria in unstructured data[10]. It emphasizes real-world data analysis for medical product evaluation and EHR data's superiority over claims data. The paper shows how machine learning can extract and structure clinical data, especially from unstructured formats, to identify health conditions accurately.

The paper addresses the critical need for effective disease prediction in healthcare using machine learning techniques. It emphasizes the potential of healthcare data in predicting diseases based on patient treatment history and health data[11]. While machine learning has been successful in tasks like billing and patient management, applying deep learning to EHR data requires further research and oversight from medical experts. Challenges include data structure, acceptance by the medical community, and the need for comprehensive patient representation before deploying predictive models. By utilizing data mining and deep learning, the study focuses on building a robust predictive model for early disease detection. The ultimate objective is to enable proactive healthcare interventions, reducing the risk to patients' lives and lowering treatment costs through early recognition and intervention.

Hence, the evolution of Electronic Health Records (EHRs) has revolutionized healthcare documentation, yet challenges remain in meeting evolving needs. While EHR adoption has surged, concerns persist regarding security, interoperability, and their impact on patient outcomes. Machine learning (ML) techniques, particularly deep learning, have shown promise in analyzing EHR data, characterizing chronic conditions, and predicting health outcomes, with the ultimate goal of enabling proactive healthcare interventions to reduce patient risk and treatment costs through early detection and intervention.

3. METHODOLOGY

The methodology for creating an Electronic Health Records (EHR) web-app involves a comprehensive approach that integrates frontend development, backend prowess, multimedia efficiency and health recommendation.

3.1Web application

The frontend development of the EHR web app begins with the creation of intuitive user interfaces using HTML, CSS, and Bootstrap. These technologies are employed to create visually attractive and intuitive interfaces that improve the overall user experience. JavaScript is then employed to add dynamic functionalities to the interfaces, making them more interactive and responsive. The backend development of the EHR web app focuses on building a robust backend infrastructure using the Java Spring Boot framework. This framework is chosen for its scalability, reliability, and security features. APIs are developed to manage data and business logic, ensuring seamless communication between the frontend and backend components of the web app. SQL is used for secure data handling, ensuring the integrity and confidentiality of sensitive information stored in the EHR system.

To enhance multimedia efficiency, the web app integrates SQL for efficient management of multimedia content such as documents and images within the EHR ecosystem. SQL enables the efficient storage, retrieval, and management of these multimedia types, ensuring that they are processed and delivered efficiently, enhancing the overall performance of the EHR web app. The EHR web app aims to provide health recommendation by analyzing unstructured EHRs in patient databases. This involves using data analysis techniques to extract meaningful insights from the unstructured data, which can then be used to generate health recommendation for individual patients. By leveraging data analysis, the web app can provide tailored health insights that are specific to each patient's unique health profile.

Therefore, the overall approach to creating the EHR web app involves combining cutting-edge technology with web development tools to innovate and redefine the landscape of Electronic Health Records systems. The web app is designed to provide holistic healthcare delivery by leveraging technology for personalized insights, ultimately improving the quality of healthcare provided to patients.

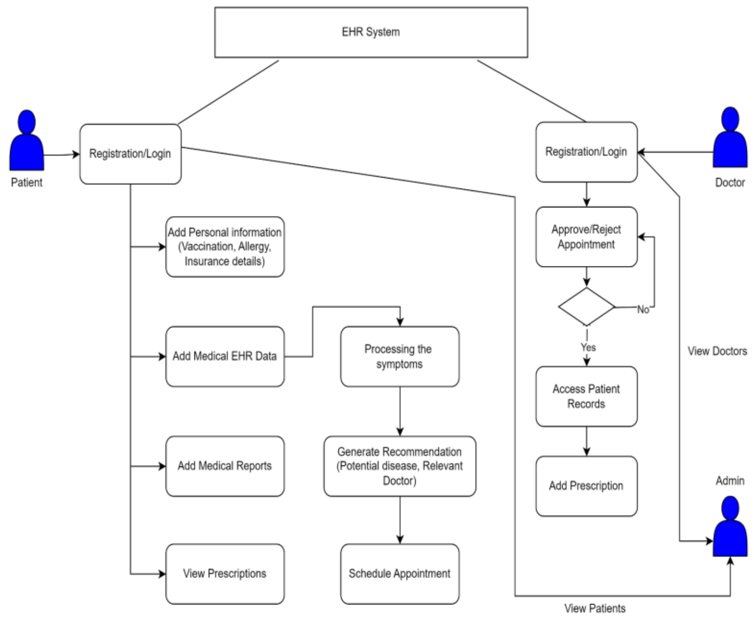

Figure 1. System Architecture of the EHR system

The system architecture of the EHR system is depicted in the above Figure1.

3.2Machine Learning Model

The methodology for the machine learning model on predicting the health recommendations from the symptoms from electronic health records (EHRs) involves several key steps The following Fig.2 shows the methodology of the ML model:

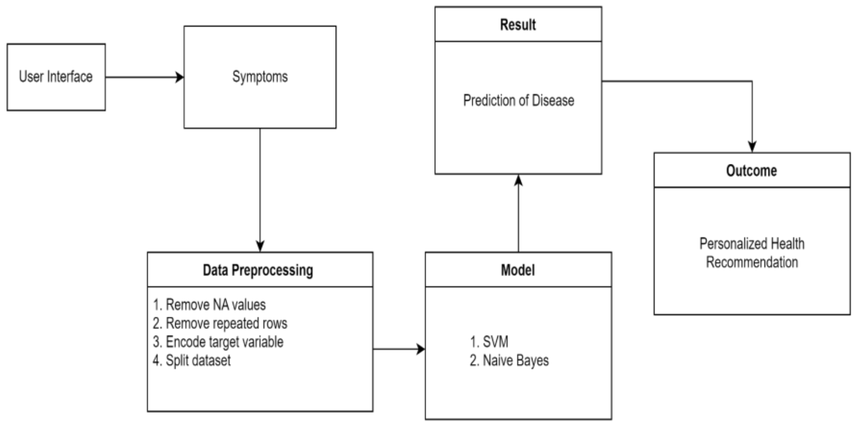

Figure 2. Machine Learning Model Methodology

3.3. Data Analysis

The dataset utilized in this study was sourced from Kaggle and was contributed by numerous young researchers globally. It comprises two CSV files: one for training the model and the other for evaluation purposes. The training dataset consists of 133 columns, where 132 columns represent symptoms, and the 133rd column represents the disease. It encompasses 42 diseases, each having 120 examples of various symptoms, resulting in a total of 5040 records. However, upon further examination, it was discovered that the original dataset contained only 3431 unique records, with the remaining 1609 records being duplicates. Removing these duplicates was crucial to prevent overfitting in the performance of the model. The following Table 1. states the description of the dataset used for the health prediction.

Table 1. Dataset description

Data Set	Number of Rows
Training Set	4032
Testing Set	1008

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3.4Data Pre-processing

Data preprocessing plays a crucial role in any machine learning endeavor, including health recommendation systems. Its primary objective is to convert data into a format that is better suited for analysis by ML algorithms. Several typical steps involved in preprocessing of data are as follows.

1. Data Cleaning: Data cleaning for handling missing values Diin the dataset and deciding how to handle them. Options include removing rows with missing values, imputing missing values with the mean or median, or using more advanced techniques like interpolation.
2. Managing Categorical Variables: When the dataset includes categorical variables, they must be converted into numerical format for processing by the model. This can be achieved through methods such as label encoding or one-hot encoding.
3. Feature Scaling: For algorithms that are influenced by the scale of features (like Naive Bayes), it's crucial to scale the features to a comparable range. Standardization (adjusting to have a mean of 0 and variance of 1) or normalization (scaling to a range between 0 and 1) are common techniques utilized for this purpose.
4. Feature Selection: It might be beneficial to perform feature selection to identify the most relevant symptoms for disease prediction. This can help reduce the dimensionality of the dataset and potentially improve model performance.
5. Addressing Imbalanced Classes: In cases where the dataset exhibits imbalanced classes (i.e., some diseases have notably fewer instances than others), methods like oversampling, undersampling, or incorporating class weights can mitigate class imbalances and enhance model efficacy.
6. Dataset Splitting: Divide the dataset into training, validation, and test subsets. The training subset is utilized for model training, the validation subset is employed for hyperparameter tuning, and the test subset is utilized to assess the final performance of the model.

Overall, data preprocessing is a crucial step for this research which includes handling missing values and feature selection where. columns with missing values are dropped using the dropna() method to ensure data integrity. The target variable prognosis undergoes numerical encoding using LabelEncoder, converting the categorical variable into a format suitable for the machine learning model. Subsequently, the dataset is divided into features (X) and the target variable (y) to facilitate model training. Then, employing the train_test_split function, the dataset is further partitioned into training and testing sets. This ensures that the model is trained on a subset of the data and evaluated on a separate subset to gauge its performance. Overall, these preprocessing steps prepare the dataset for training machine learning algorithms by handling missing values and standardizing existing features. These steps are instrumental in enhancing the model's performance and its capacity to accurately predict diseases based on symptoms, thereby offering optimal recommendations.

3.5Model Selection

In this project, the dataset goes through preprocessing steps such as handling missing values. Standardization is then applied to prepare the features that are relevant in prediction. Various ML methods can be employed for delivering health recommendations. These methods utilize algorithms to learn from labeled data and subsequently classify new data based on identified patterns. Typical ML techniques include Naive Bayes and Support Vector Machines.

a) Naive Bayes

Naive Bayes is a probabilistic classifier derived from Bayes' theorem, often employed for disease prediction based on symptoms [12]. In this scenario, the algorithm operates under the assumption that the occurrence of a specific symptom is unrelated to the occurrence of any other symptom, given the disease. Here's how the algorithm functions:

1. In a training dataset D containing documents categorized into different classes (Class A and Class B), the algorithm computes the prior probability of each class. This is achieved by dividing the number of instances in each class by the total number of instances in the dataset.

$$\mathrm{P(Disease)} = \frac{\mathrm{count(Disease)}}{\mathrm{total\_count}}$$

2. The algorithm then calculates the total frequency of each disease (N_Disease), which is the sum of the frequencies of all records corresponding to that disease.

$$\mathrm{N_{Disease}} = \sum_{\mathrm{i=1}}^{\mathrm{Count}} \quad (\mathrm{Disease_i})$$

3. Next, the algorithm calculates the conditional probability of a symptom occurrence given a disease. For each symptom (value), the algorithm calculates the count of that symptom in each disease and divides it by the total frequency of that disease (N_Disease) to get the probability of the symptom occurring given the disease.

$$p\big((\text{Disease})\big) = \frac{\text{count}\big((\text{Disease})\big)}{\text{N}}$$

4. To avoid the zero-frequency problem, the algorithm applies a smoothing technique such as Laplace smoothing, which adds a small non-zero probability to all features.
5. To classify a new set of symptoms, the algorithm assesses the likelihood of each disease considering the symptoms (P(Disease|Symptoms)) based on the prior probabilities and the conditional probabilities of symptoms occurring given the disease. It multiplies these probabilities together for each symptom in the input.

$$\text{P(Disease|Symptoms)} = \text{P(Disease)} * \prod \text{P(value|Disease)}$$

6. Finally, the algorithm assigns the set of symptoms to the disease with the highest probability.

In summary, Naive Bayes is a simple yet effective algorithm for disease prediction based on symptoms. It assumes that symptoms are independent given the disease, which is a naive assumption but often works well in practice, especially when the dataset has a large number of symptoms.

After preprocessing, the Naive Bayes algorithm is applied to the dataset to predict diseases based on symptoms. Naive Bayes is a probabilistic classifier that calculates the probability of each disease given the input symptoms. It assumes that the presence of each symptom is independent of the presence of other symptoms given the disease. The algorithm calculates the likelihood of each symptom occurring in each disease based on the training data and uses Bayes' theorem to determine the most likely disease for a given set of symptoms. This prediction process is repeated for each instance in the dataset, resulting in a prediction for each individual's disease based on their symptoms.

b) Support Vector Machines (SVM)

SVM is a supervised ML method utilized for classification and regression applications[13].
1. SVM aims to find the hyperplane w·x+b=0 that best separates different types of diseases in the feature space defined by the symptoms.
2. SVM employs a kernel function to transform the input symptoms into a higher-dimensional space where linear separation is achievable. This enables SVM to handle non-linearly separable data and find complex decision boundaries between classes.
3. Given a training dataset with labeled samples, SVM learns the optimal hyperplane by maximizing the margin between classes. It selects a subset of training samples, called support vectors, that are nearest to the hyperplane influencing its position. The optimisation goal is to minimize the error of classification while maximizing the margin, which is commonly written as a convex optimisation problem.
4. SVM supports various kernel functions like linear, polynomial, sigmoid, and radial basis function (RBF). These kernels enable SVM to address both linearly inseparable and non-linearly separable data.
5. SVM uses a regularization parameter (C) to strike a compromise between maximizing margin and minimizing classification errors on training data. A higher C value results in a smaller margin and fewer misclassifications, whereas a lower value allows for a bigger margin and more misclassifications.
6. After training, SVM can predict the presence or absence of a disease for new patients based on their symptoms. The algorithm assigns a new patient to a disease class based on which side of the hyperplane the patient's symptoms fall on.

In summary, SVM is a powerful algorithm for disease prediction based on symptoms, capable of handling non-linear relationships and finding optimal decision boundaries between classes. It is particularly useful when the relationship between symptoms and diseases is complex and not easily separable by a linear classifier.

After preprocessing, the SVM algorithm is applied for disease prediction based on symptoms. SVM seeks to identify the hyperplane which best divides the data into various disease classes by maximizing the margin between the classes. The decision boundary is determined using the support vectors, which represent the data points nearest to the hyperplane. This allows SVM to predict the most likely disease for each individual based on their symptoms.

c) Recommendation

The specialist recommendation involves mapping predicted diseases to specialized medical practitioners. This process ensures that patients receive appropriate care from the most relevant healthcare professionals. The process for specialist recommendation involves the following steps:

1. Disease Prediction: After preprocessing the dataset and training the ML models (e.g., Naive Bayes, Support Vector Machine) to predict diseases from symptoms, the system obtains the predicted disease for a given set of symptoms.
2. Mapping Diseases to Specialists: A lookup table or database is created to associate each predicted disease with the corresponding specialist. This mapping is based on the medical field or expertise required for treating the disease. For example, a cardiologist may be recommended for cardiovascular diseases, while a dermatologist may be recommended for skin conditions.
3. Recommendation Process: When a disease is predicted for a patient, the corresponding specialist from the lookup table or database is retrieved by the system. The recommendation is then displayed to the user, indicating the type of doctor they should consult for further evaluation and treatment.
4. Additional Information: Along with the specialist recommendation, the system may provide additional information about the predicted disease, such as common symptoms, treatment options, and preventive measures. Patients who use this information can make more educated decisions regarding their treatment and have a better understanding of their situation.
5. User Interaction: The specialist recommendation is integrated into a user-friendly interface, EHR web app. Users can input their symptoms, receive a predicted disease, and view the recommended specialist with ease.

By integrating disease prediction with specialist recommendation, the system aims to improve healthcare delivery by guaranteeing that patients receive prompt and adequate treatment from the qualified healthcare professionals.

d) Evaluation Metrics

The confusion matrix, widely employed and appropriate for assessing classifiers, is a tabular representation that evaluates their performance by contrasting predicted outcomes with actual values. Table 2 illustrates a broader version of the confusion matrix.

Table 2. Confusion Matrix

	Predicted class 1	Predicted class 2
Actual class 1	True Positive	False Negative
Actual class 2	False Positive	True Negative

The method enables the derivation of comprehensive evaluation metrics, encompassing the following parameters [14]:

● Accuracy: This measure evaluates a classifier's total accuracy, indicating the precision of its predictions. Eq. 1 provides the formula for calculating the classifier's accuracy.

$$\text{Accuracy} = \frac{\text{True Positive}+\text{True Negative}}{\text{Total Predictions}} \quad (1)$$

● Precision: This measure assesses how well a model predicts the future positively. Put another way, precision shows how accurate the model is in making positive predictions by expressing the percentage of accurate positive predictions among all the positive predictions that are produced. Eq. 2 provides the precision formula.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive}+\text{False Positive}} \quad (2)$$

● Recall: This metric evaluates a model's ability to pinpoint every favorable case. To clarify, it refers to the model's true positive predictions divided by all actual positive cases in the dataset. Eq. 3 presents the formula for recall.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive}+\text{False Negative}} \quad (3)$$

● F1-score: This measure evaluates the accuracy of a model by combining recall and precision into a single score. A weighted average of recall and precision, ranging from 0 to 1, is used to compute this score. The model's performance is assessed using the F1 score, which also helps choose the best balance between precision and recall. Eq. 4 provides the formula for the F1 score.

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision+Recall}} \quad (4)$$

4. RESULTS AND DISCUSSION

The research sought to examine how machine learning algorithms could predict health outcomes using a dataset containing extensive symptom data for various diseases. The performance of ML models, such as SVM and Naive Bayes, in the Electronic Health Record (EHR) system is shown in Table 3. The evaluation criteria encompasses various evaluation metrics.

Table 3. Comparing the Performance of Different Models

Models	Evaluation Metrics			
	Accuracy	Precision	Recall	F1-Score
SVM	0.9493	0.93	0.93	0.93
Naive Bayes	0.9855	0.97	0.96	0.97

Table 4 Illustrates the study's accuracy achieved across both ML algorithms.
table IV. Accuracy Evaluation using various Algorithms

Training Data	Testing Data	Using SVM	Using Naive Bayes
4032	1008	94.93	98.55

The assessment metrics of the different models on the test data are shown in Figure 3.

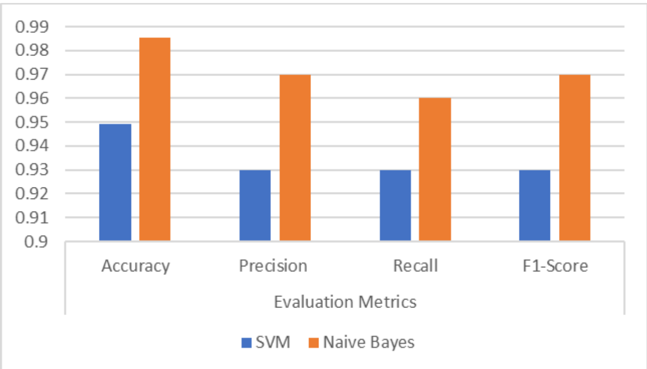

Figure 3. Classifier Evaluation Metrics on Test Data

The findings indicate that both ML algorithms tested showed satisfactory performance in health recommendation. Consistently high accuracy scores across models imply their ability to accurately classify outcomes. When comparing algorithms, Naive Bayes stood out with the highest accuracy at 98.55%, suggesting its robustness. In addition, the evaluation of health prediction was conducted using precision, recall, and F1-Score. Naive Bayes demonstrated superior precision, recall, and F1-Score, which might be critical depending on the circumstances. SVM also yielded commendable results across all evaluation metrics.

5. CONCLUSION

Incorporating electronic health records (EHR) with machine learning methods such as Naive Bayes and Support Vector Machines (SVM) introduces an innovative approach to healthcare management. This combination offers significant potential for improving patient care through streamlined record management, enhanced data accuracy, and personalized health recommendations derived from comprehensive patient health data. This research highlights the transformative impact of predictive healthcare analytics on disease prevention, early intervention, and customized patient care. By addressing the drawbacks of manual record-keeping and leveraging technology to provide personalized health insights, this method strives to enhance patient outcomes and elevate healthcare quality. Nonetheless, it's essential to tackle obstacles like data privacy and algorithm transparency to guarantee the ethical and efficient application of predictive models in clinical environments. Ultimately, the fusion of EHRs with machine learning offers the potential to transform healthcare management, bringing about improvements in patient care, disease prognosis, and tailored healthcare provision.

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