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Research Article

Predicting Optimal Chemotherapy Regimens in Breast Cancer Treatment using Machine Learning

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ABSTRACT

Breast cancer treatment involves personalized chemotherapy regimens to improve patient outcomes, and selecting the optimal regimen is a crucial challenge. Machine learning (ML) algorithms offer potential solutions by analyzing complex clinical data and predicting effective treatment strategies. This study conducts a comparative analysis of multiple ML algorithms, including decision trees, support vector machines, neural networks, and ensemble methods, to predict the optimal chemotherapy regimens for breast cancer patients. Using a dataset comprising clinical, pathological, and molecular features, the models are trained and evaluated based on accuracy, sensitivity, specificity, and predictive power. The results demonstrate that ensemble methods outperform other approaches, offering higher prediction accuracy and robustness. Feature importance analysis further highlights significant predictive factors for chemotherapy response. This comparative study provides valuable insights into the strengths and limitations of various ML algorithms in the context of personalized chemotherapy for breast cancer, contributing to more informed decision-making and potentially enhancing treatment efficacy.

Keywords: SVM, ANN, Gradient boost, CV.

1. INTRODUCTION

Breast cancer remains one of the most prevalent cancers among women globally and is a significant public health concern. Advances in treatment have led to improvements in survival rates; however, chemotherapy remains a cornerstone for treating many breast cancer patients. Selecting the optimal chemotherapy regimen is critical for maximizing therapeutic efficacy while minimizing adverse effects, given the variability in patient response due to factors such as genetic heterogeneity, tumor characteristics, and individual patient profiles. Traditional approaches to determining chemotherapy regimens rely on standardized guidelines, clinician experience, and biomarkers. However, these methods often face limitations when applied to the diverse patient population, leading to suboptimal outcomes for some individuals. The need for more personalized treatment has spurred interest in predictive models capable of assisting Oncologists in selecting the most effective chemotherapy regimen. Machine learning (ML), with its ability to learn complex patterns from large datasets, holds considerable promise in this context. ML techniques have been successfully applied to various aspects of cancer research, including prognosis, diagnosis, and treatment prediction. By leveraging clinical, pathological, and molecular features, ML algorithms can potentially predict treatment response with high accuracy, aiding in personalized chemotherapy regimen selection.This study aims to conduct a comparative analysis of multiple ML algorithms—such as support vector machines, neural networks, and ensemble methods—to predict the optimal chemotherapy regimen for breast cancer patients. By evaluating these algorithms in terms of predictive accuracy, sensitivity, and specificity, we aim to determine which approach best supports personalized treatment decisions, ultimately enhancing patient outcomes and reducing the burden of unnecessary side effects. This comparative analysis also seeks to provide insights into the most influential factors contributing to chemotherapy success, thus supporting the continued development of data-driven precision oncology.

2. RELATED WORK

In 2024, Keikhosrokiani, P., Balasubramaniam, K., Isomursu, has published paper " Drug Recommendation System for Healthcare Professionals' Decision-Making Using Opinion Mining and Machine Learning" were Sentiment analysis and hybrid content-based and collaborative filtering algorithms implemented. The bi-channel heterogeneous local structural encoder proposed by Zhang et al. (2023) is a significant contribution to this domain, providing a method to extract and utilize the diverse information embedded in HINs. The work by Swati Dongre and Jitendra Agrawal (2023) presents a novel healthcare model that leverages deep learning to analyze social media posts for drug recommendation and ADR detection. A.S. Mallesh (2022) proposed a decision support platform for drug rating generation and recommendation using sentiment analysis of drug reviews.Satvik Garg,(2021)were implemented Drug Recommendation System based on sentiment analysis of drug reviews using machine learning Uses patient review to predict drugs using sentiment analysis BOW,TD-IDF method. The research by Deloar Hossain and Shafiul Azam proposes a system to generate drug ratings and provide recommendations based on sentiment analysis of patient reviews using machine learning. The approach utilizes a Linear Support Vector Classifier (SVC) to analyze drug reviews and generate ratings, enabling effective drug recommendations. Wen-Hao Chiang's study focuses on developing a drug recommendation system aimed at ensuring safe polypharmacy, which involves the use of multiple drugs simultaneously. The research addresses the challenge of predicting adverse drug reactions (ADRs) that may arise from drug combinations.

3. METHODOLOGY

3 methods used here Support vector machine, Gradient boost and artificial neural network

1. Support vector machine:

In this first Feature extraction and data preprocessing to obtain the feature vector, $x_i \in R^n$ and labels $y_i \in \{-1,1\}$ .and then use a kernel function $\emptyset(x)$ *to* transform data into a higher-dimensional space if needed for linear seperability. Find the optimal hyperplane that maximizes the margin. Solve the optimization problem using Lagrange multipliers to determine w and b. Classify new data point's x using the decision function $(x) = Sign(wT\emptyset(X) + b$.

2. Gradient boost method:

2. Gradient boosting is an ensemble machine learning technique that sequentially combines the predictions of multiple weak learners, usually decision trees. Its goal is to enhance overall predictive performance by iteratively adjusting the model's weights based on the errors from previous iterations. By gradually reducing prediction errors, gradient boosting aims to improve the accuracy of the model over time.

Steps:

1. $F_0(x) = \text{argmin} \sum_{i=1}^{n} L(y_{i,} \gamma)$(L is our loss function)

2. For m=1 to M:

Compute residual $r_{im=-}\left[\frac{\partial \mathrm{L}(y_i, \mathrm{F}(x_i))}{\partial \mathrm{F}(x_i)}\right]_{f(x)=F_{m-1}(x)}$ for i=1,...n

2.2 Train regression tree with features x against r and create terminal node reasons R_{jm} for j-1, ...J_M

2.3 Compute

$r_{jm=}\text{argmin} = \sum_{x_i \in R_{jm}} L(y_{i,} F_{m-1}(x_i) + \gamma)$for j=1,....$J_m$

2.4 update the model

$$F_m(x) = F_{m-1}(x) + \sum_{j=1}^{Jm} \gamma_{jm1}\, 1(x \in R_{jm})$$

4. ARTIFICIAL NEURAL NETWORK:

Data Preparation: The data is pre-processed and fed into the input layer of the network. In the image, this is represented by the x1 to xn values. Forward Propagation: The data travels through the network, layer by layer. At each layer, the artificial neurons process the data using a mathematical function. This function typically involves applying weights to the inputs, summing them, and then passing the sum through an activation function. The activation function introduces non-linearity into the network, allowing it to learn complex patterns. Hidden Layers: The hidden layers are where most of the computation takes place. There can be multiple hidden layers, each containing many artificial neurons. These layers extract features from the data and progressively transform it towards the desired output. Output Layer: The processed data reaches the output layer, where it is transformed into a final output signal. This output could be a classification (e.g., cat or dog), a prediction (e.g., house price), or a control signal (e.g., robot movement).Backpropagation: In training mode, the algorithm compares the output of the network to the desired target output. If there's a difference (error), the error is propagated backward

5. PROPOSED SYSTEM:

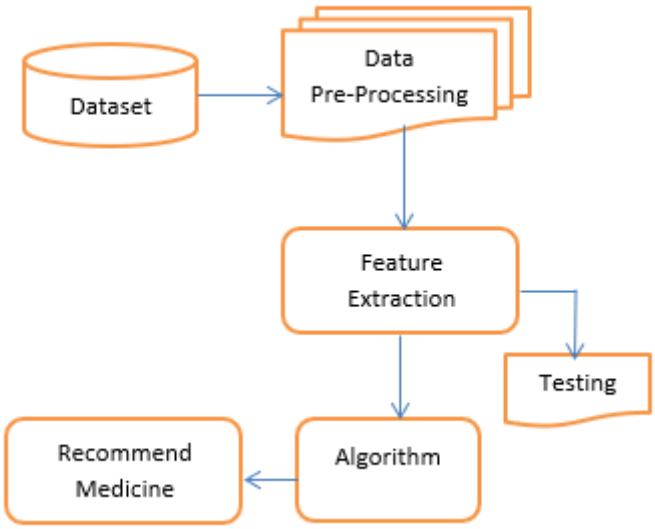

Fig.1.System Architecture

This proposed system is divided into two parts as given in fig.1 that is mention as 1.the training phase and (2) the validation phase. Both phases are crucial for achieving accurate predictions. In this proposed system we search the best medicine for chemotherapy for breast cancer. There are 4 medicine here we use those are carboplatin, Cyclophosphamide, fluorouracil, Doxorubicin. This System predicts best medicine for the chemotherapy of Brest cancer. Here proposed systems have good accuracy when compare with SVM, Gradient boost, ANN, Grid search methods.

Data preprocessing: is crucial for preparing a dataset for machine learning by handling missing values, encoding categorical variables, scaling features, and addressing class imbalances. This ensures the breast cancer dataset is clean, consistent, and optimized for accurate model predictions.

Feature extraction: transforms raw data into informative features, improving machine learning model performance. In a breast cancer dataset, this involves deriving new features or applying domain-specific knowledge to create meaningful attributes for better predictions.

Splitting the dataset: into training and testing sets is a critical step in the machine learning workflow. This allows the model to be evaluated on unseen data, offering a realistic measure of its performance. In this approach, 80% of the dataset is used for training the model, while 20% is set aside for testing.

Training &Testing: The machine learning model is trained using the training data to learn patterns and relationships. Once trained, the model's accuracy and generalization capability are evaluated using the testing

data, providing insights into its real-world performance.

6. EXPERIMENTS

This Experiment section discuses and evaluates performance of new proposed model. It uses Data Set for performance evaluation.

Dataset:

The proposed model is simulated breast cancer datasets .data set consist of 3326 patient data with 8 features.

Performance Evaluation:

By Comparing against SVM, Gradient boosting, Artificial Neural Network ,Grid search Classifier with proposed model then measure the performance. For more development and assessment of model dataset, it was randomly divided into training (80%) and testing (20%) subsets.

Evaluation Metrices:

Five Metrics are used her for evaluation are precision (Prec), recall (Rec), F1-score (F1), accuracy (Acc.).

7. RESULT

In this system we discuss on the proposed ensemble deep learning model achieved an accuracy of 96% on dataset. This outperforms both the Support Vector Machine (SVM) which achieved 77% accuracy and the Gradient Boosting classifier which reached 87.6% accuracy.In result here calculated for 4 medicines which is used in chemotherapy test and from that four medicine one perfect medicine predicted by the system.Table1.shows result for carboplatin medicine

Classifier	Acc (%)	Pre (%)	Rec (%)	F-score (%)
Svm	70%	0.70	1	0.83
Gradient Boost	70%	0.70	1	0.83
ANN	80%	0.85	0.88	0.86
Proposed Model	90%	0.90	0.92	0.93

Table1.Result for Cyclophosphamide medicine

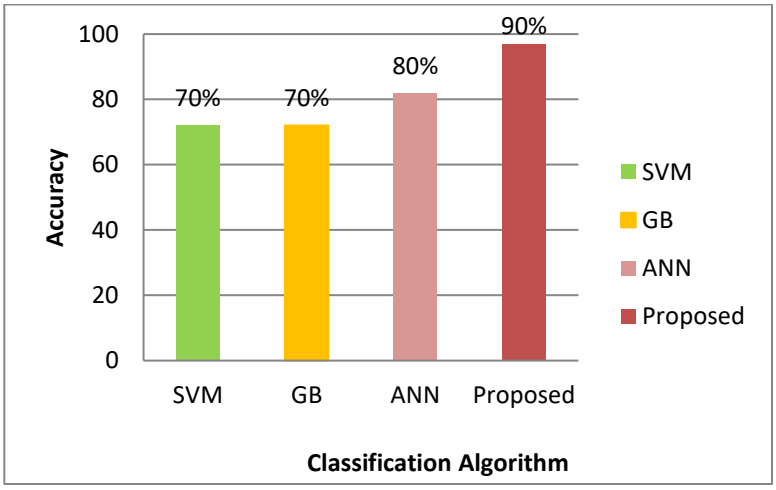

Fig2.Accuracy Result for Cyclophosphamide medicine

Table 1 presents the results for the cyclophosphamide medication, comparing the performance. The prediction results for cyclophosphamide depicted in Figure 1; confirm that the highest accuracy is achieved with this method.

Classifier	Acc (%)	Pre (%)	Rec (%)	F-score (%)
Svm	73	0.73	1	0.85
Gradient Boost	73	0.73	1	0.85
ANN	81	0.85	0.91	0.88
Proposed Model	96	0.97	0.99	0.97

Table2.Result for fluorouracil Medicine

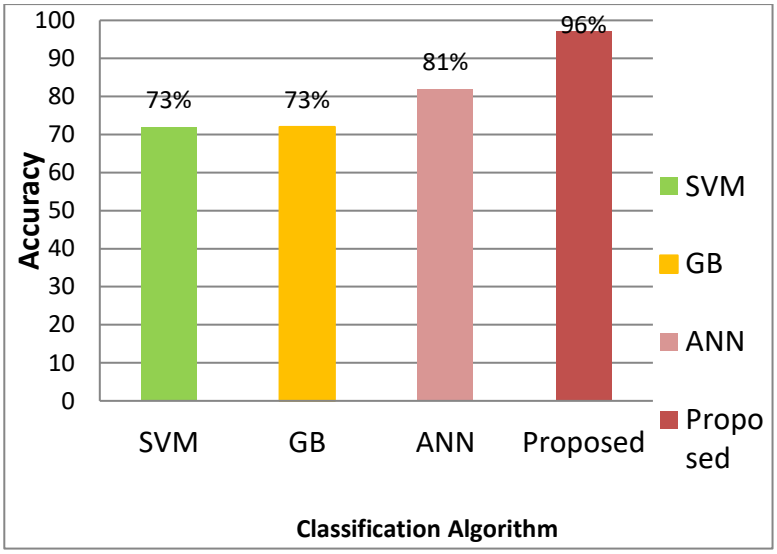

Fig2.Accuracy Result for fluorouracil medicine

Fig2.predict fluorouracil has highest accuracy i.e. 96%

Classifier	Acc (%)	Pre (%)	Rec (%)	F-score (%)
Svm	72%	0.72	1	0.84
Gradient Boost	72%	0.72	1	0.84
ANN	82%	0.83	0.95	0.89
Proposed Model	97%	0.97	1	0.98

Table3 .Result for Doxorubicin medicine

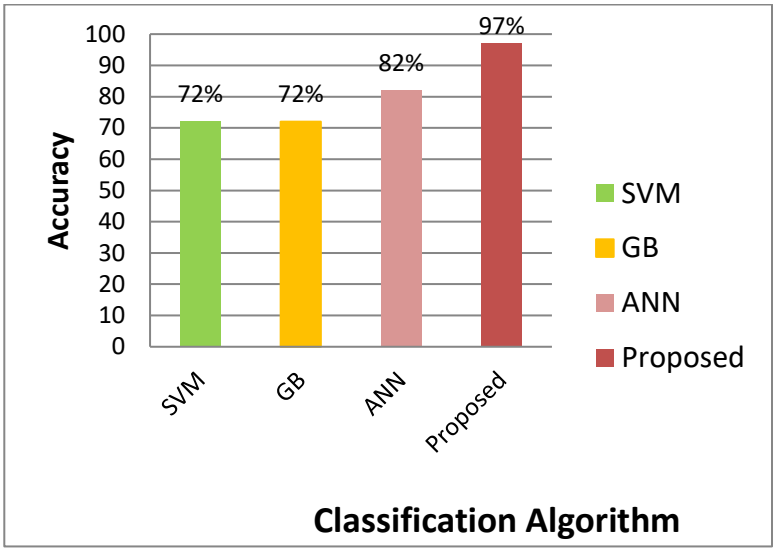

Fig2.Accuracy Result for Doxorubicin medicine

Graph shown in fig3 predict Doxorubicin have highest accuracy i.e. 97%

Classifier	Acc (%)	Pre (%)	Rec (%)	F-score (%)
Svm	77%	0.77	1	0.87
Gradient Boost	77%	0.77	1	0.87
ANN	84%	0.85	0.97	0.90
Proposed Model	98%	0.99	1	0.99

Table 4.Result for Carboplatin medicine

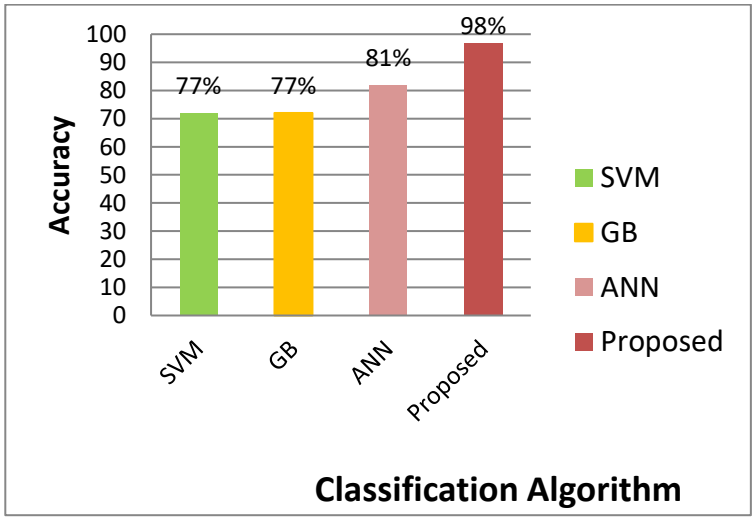

Fig4 Result for Carboplatin medicine

Graph shown in fig4 .predict carboplatin have highest accuracy.

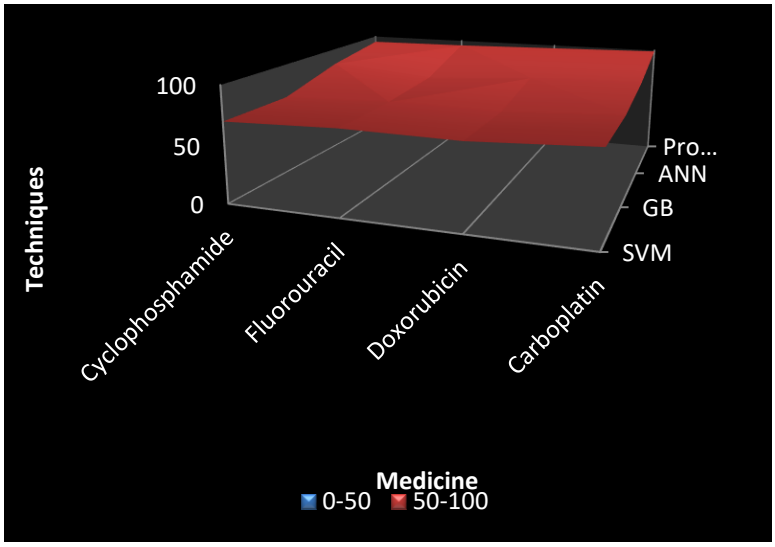

Fig5.prediction of best Medicine (Carboplatin)

As per all result prediction we conclude that carboplatin is best medicine for breast cancer therapy as per graph shown in Fig.5carboplatin has highest accuracy 98%.

8. CONCLUSION & FUTURE SCOPE

The proposed system introduces a novel approach to aid healthcare professionals in patient care by offering recommendations for potential medications suitable for treatment. What sets our recommendation system apart is its ability to provide easily interpretable suggestions. By analyzing medications previously administered to patients with similar characteristics to the current patient, our system generates recommendations that are intuitively understandable. This ensures that healthcare personnel can readily grasp the rationale behind each suggested medication, facilitating informed decision-making in medical care. The future of ML in predicting optimal chemotherapy regimens lies in creating intelligent, adaptive, and ethical systems that empower clinicians and improve patient outcomes. With advancements in data integration, algorithm design, and clinical implementation, ML has the potential to transform breast cancer treatment into a highly precise and personalized science.

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Author Contributions

Dr. Mahesh R.Sanghavi contributed equally to the conceptualization, methodology, data analysis, and writing of this article.

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Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request

Has this article screened for similarity?

Yes

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