PREDICTING POOR COMPLIANCE TO PSYCHOTROPICS USING MACHINE LEARNING APPROACH

BY

DHRUBANG UTPAL TALUKDAR (CSB20049)

UNDER THE GUIDANCE OF

DR. ROSY SARMAH,
ASSOCIATE PROFESSOR,
DEPARTMENT OF CSE,
TEZPUR UNIVERSITY

DR. SIDDESWARA BL,
ASSISTANT PROFESSOR,
DEPARTMENT OF CHILD AND ADOLESCENT PSYCHIATRY,
LGBRIMH

Content

- Abstract
- Introduction
- Problem Definition
- Planning
- Results
- ML Tool Building

Abstract

- Predicting poor medicine compliance in pediatric mental health is crucial.
- Work is an outcome of a collaborative project with LGBRIMH, Tezpur
- Propose an ensemble-based feature selection to reduce features for classification.
- Evaluated 5 models: KNN, SVM, Random Forest (RF), AdaBoost, and XGBoost.
- RF gave the best results.
- Developed two modified RF versions: Meta RF (ensemble of RFs) and RF using weighted entropy.
- Developed an ML tool incorporating our feature selection, created from a dataset of 470 children with mental health issues, showing predicted compliance to clinicians.

Introduction

- Non-compliance with psychotropic medications can lead to severe consequences, including worsened mental health, increased hospitalizations, and suicidal thoughts.
- Accurate predictions help clinicians intervene early, improving treatment outcomes and reducing long-term health complications.
- A machine learning (ML) tool can analyze complex patterns in datasets, providing precise and personalized compliance predictions.
- This enhances the efficiency of healthcare delivery, reduces treatment costs, and supports better health management for vulnerable pediatric populations. Ensuring adherence can significantly improve quality of life for children with mental health disorders.

Problem Definition

Objective:

- Predicting medication compliance in advance for children.

Goals:

- Analyze factors which influence low compliance in children.
- Develop a user friendly interface to be used by clinicians.

Planning

DATA COLLECTION

Get the required data of children suffering from various mental health issues from Lokopriya Gopinath Bordoloi Regional Institute of Mental Health

DATA CLEANING AND PREPROCESSING

This typically includes tasks such as handling missing values, removing duplicates, appropriate data conversion.

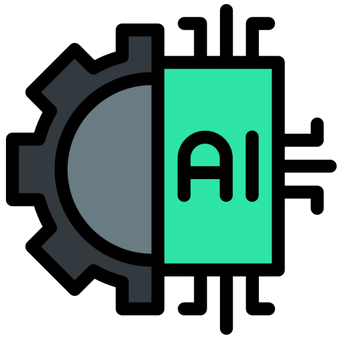
FEATURE ENGINEERING

Feature engineering is the process of creating new features or transforming existing ones from raw data to enhance the performance of machine learning models

Planning

FEATURE RANKING

Feature ranking involves evaluating the importance or relevance of features in a dataset to prioritize them based on their contribution to the predictive power of machine learning models, aiding in feature selection and interpretation



Analyze and compare the various supervised machine learning algorithms based on various evaluation metrics.

SUPERVISED MACHINE LEARNING ALGORITHMS

CREATE ML TOOL

Use the best algorithm and create a ML tool to predict compliance on basis of various inputs.

Data Collection

The dataset, collected from Lokopriya Gopinath Bordoloi Institute of Mental Health in Tezpur, Assam, India which includes 150 records with 248 attributes initially. It encompasses personal details (e.g. name, age, gender), medical history, family medical background, treatment details, and compliance metrics (e.g. mean gap ratio, medication possession ratio, follow-ups). Compliance is categorized as Good, Satisfactory, or Poor.

Later we received the final dataset comprising 470 rows with 248 attributes.

Data Preprocessing and Cleaning

To prepare the dataset, attributes with mostly null values and irrelevant information like Name and Unique ID were removed. Missing numerical values were filled with zeros, and textual attributes were converted to numerical values via mapping. This ensured a robust, consistent dataset for analysis.

Feature Engineering

- In our study, we expanded our dataset by adding 14 new features representing various prevalent mental health states, derived from frequently diagnosed conditions. These features include irritability, anger, abnormal behavior, restlessness, jerky movements, mood fluctuations, outbursts, eye contact patterns, cognitive impairments, anxiety levels, hallucinatory experiences, depressive symptoms, seizures, and ADHD tendencies.

- All unnecessary attributes were dropped and the final dataset contains 73 features.

Feature Ranking

Used Methods :

- Random Forest
- Mutual Information
- Pearson Correlation
- Ensemble of Random Forest, Mutual Information and Pearson Correlation

Feature Ranking using Random Forest, Mutual Information and Pearson Correlation

Rank	Feature	Random Forest Importance
1	Off-medications duration (to add all such durations over follow-up in days)	0.1411981135413449
2	Maximum duration of symptom free period (in days)	0.12431624810669437
3	Maximum period of compliance at lgb (in days) (longest streak of good compliance)	0.06602369826781676
4	Total frequency	0.0517838366690728
5	Total duration of medication treatment at LGB (in days) (from first consultation to last follow-up)	0.05125419746268719
6	Mean gap ratio at lgb (total no of months of follow-up divided by no of follow-ups)	0.03678817275838798
7	Days/freq	0.03415253264063216
8	Continued medication 2/stopped/changed	0.03159955047408112
9	Total number of follow up at LGBRIMH	0.0264160190425899
10	Age at presentation (in yrs)	0.026211943197286612
11	Medication possession ratios 1 (MPRs) in lgb;x-syrup (total number of days when medications were taken divided by summation of total number of days when medications were taken with total off medication period)	0.025584796768803743
12	Distance from LGBRIMH (in KM)	0.024753239692615146
13	Total duration of medication 2 (in days)	0.02316438040148189
14	Age at last follow up	0.02238922928261885
15	Time period between onset to first consultation at LGBRIMH (DUI) (in days)	0.019199562921172093
16	No of relapses/exacerbations	0.018437110075078752
17	Total duration of medication 1 (in days)	0.017218406048751512
18	Max Duration of resolution of symptoms before re-currence/relapse (in days)	0.01698400239089499
19	Response to medication 2 (Good/partial/no)	0.016617095907808 32
20	weight (in Kg)	0.015265144841052245
21	Maximum dose of medication 1 (in mg)	0.014714196464566736
22	$total_{d}ays1$	0.014325717648138194
23	Age at onset (in years)	0.014314377827724583
24	Continued medication 1/stopped/changed	0.011645831255609895
25	Avg dose of medication 1 (Mode value of medication) (in mg)	0.011516864505050956
26	Response to medication 1 (Good/partial/no)	0.009850595733713495
27	School Adjustment	0.009822968315119293
28	Systemic examination (abnormal/normal)	0.008262147454874743
29	"If yes, after how many days from first presentation diagnosis changed (in days)"	0.00813615598242771
30	Past/Current medical conditions	0.006625903020411289
31	Religion	0.006085997928024703
32	significant psychosocial stressor	0.005964651005825684

Feature Ranking using Random Forest

Rank	Feature	Mutual Information
1	Off-medications duration (to add all such durations over follow-up in days)	0.15199382977124554
2	Total duration of medication 2 (in days)	0.11418086360904578
3	Outbursts	0.10202544215629405
4	Rural/Urban	0.08323417065300065
5	Eye contact	0.0828264874628033
6	Medication possession ratios 2 (MPRs) in lgb; x-syrup	0.07528851329080899
7	Maximum period of compliance at lgb (in days) (longest streak of good compliance)	0.07144738359691871
8	Age at last follow up	0.0709626816106268
9	Response to medication 1 (Good/partial/no)	0.07045454013349906
10	Total duration of medication treatment at LGB (in days) (from first consultation to last follow-up)	0.06466487948528066
11	Depression	0.06423525439763456
12	Age at presentation (in yrs)	0.05947054175456934
13	Cost of medication	0.05664344733033788
14	Total number of follow up at LGBRIMH	0.0563705399636647
15	Total frequency	0.05544669369186739
16	Restlessness	0.05531541675843599
17	Seizure	0.05377922764803511
18	Religion	0.050984523113708935
19	Continued medication 1/stopped/changed	0.04814664733310181
20	Weight (in Kg)	0.04482567710446972
21	Anxious	0.032978642280470094
22	Mean gap ratio at lgb (total no of months of follow-up divided by no of follow-ups)	0.030376647463925543
23	Total_days1	0.029392228730604764
24	Low	0.02604719712880188
25	Max Duration of resolution of symptoms before re-currence/relapse (in days)	0.023676729501421967
26	Maximum dose of medication 1 (in mg)	0.02275437750387077
27	Days/freq	0.022019259183145845
28	No of relapses/exacerbations	0.017687669855306343
29	Number of In patient cares	0.017441071976846967
30	School Adjustment	0.01642291955327524
31	Total duration of medication 1 (in days)	0.013806029062825687
32	Time period between onset to first consultation at LGBRIMH (DUI) (in days)	0.013653748847653358

Feature Ranking using Mutual Information

Rank	Feature	Pearson Correlation
1	Maximum period of compliance at lgb (in days) (longest streak of good compliance)	0.29174415501789064
2	Maximum duration of symptom free period (in days)	0.28907008188694683
3	Total number of follow up at LGBRIMH	0.2838694431557081
4	Total frequency	0.27691896205943134
5	Max Duration of resolution of symptoms before re-currence/relapse (in days)	0.27608481799631185
6	Days/freq	0.2361279301759304
7	Total duration of medication treatment at LGB (in days) (from first consultation to last follow-up)	0.20256315471696631
8	Total duration of medication 1 (in days)	0.19581960305646865
9	Continued medication 2/stopped/changed	0.19396400471150815
10	Depression	0.1542450475388608
11	School Adjustment	0.13049360904668825
12	Outbursts	0.11869251807472944
13	Total duration of medication 2 (in days)	0.11381984234593333
14	Follow up diagnosis changed or not (yes/no)	0.1068814275690267
15	Rural/Urban	0.0998302239653285
16	Type of Family (Nuclear/Joint/single parent/orphan/foster family)	0.09508094653995165
17	Distance from LGBRIMH (in KM)	0.0908098260757003
18	Age at onset (in years)	0.0907277376907143
19	Age at presentation (in yrs)	0.09032203469111426
20	Continued medication 1/stopped/changed	0.08877473718585199
21	Low	0.08550728433105109
22	Off-medications duration (to add all such durations over follow-up in days)	0.08400450606981842
23	ADHD	0.08369454941149343
24	Number of In patient cares	0.08245465921621781
25	Past/Current medical conditions	0.08213997055454715
26	Medication possession ratios 1 (MPRs) in lgb	0.08200574009693978
27	Mean gap ratio at lgb (total no of months of follow-up divided by no of follow-ups)	0.07968451118414194
28	Systemic examination (abnormal/normal)	0.07468509004981613
29	Medication possession ratios 2 (MPRs) in lgb	0.07262398522397875
30	Total_days1	0.0720072875979988
31	Sex (m/f)	0.07106173422413431
32	No of relapses/exacerbations	0.07042271192097925

Feature Ranking using Pearson Correlation

Feature Ranking using Random Forest, Mutual Information and Pearson Correlation

Rank	Feature Name
1	Maximum period of compliance at LGB (in days) (longest streak of good compliance)
2	Total number of follow up at LGBRMIMH
3	Maximum duration of symptom free period (in days)
4	Days/freq
5	Total duration of medication treatment at LGB (in days) (from first consultation to last follow-up)
6	Off-medications duration (to add all such durations over follow-up in days)
7	Total duration of medication 2 (in days)
8	Mean gap ratio at LGB (total no of months of follow-up divided by no of follow-ups)
9	Medication possession ratios 1 (MPRs) in LGB
10	Total duration of medication 1 (in days)
11	Age at presentation (in yrs)
12	Continued medication 2/stopped/changed
13	School Adjustment
14	Total_days1
15	No of relapses/exacerbations
16	Max Duration of resolution of symptoms before recurrence/relapse (in days)
17	Age at onset (in years)
18	Maximum dose of medication 1 (in mg)
19	Rural/Urban
20	Age at last follow up
21	Medication possession ratios 2 (MPRs) in LGB
22	Outbursts
23	Continued medication 1/stopped/changed
24	Distance from LGBRMH (in KM)
25	Follow up diagnosis changed or not (yes/no)
26	Family environment
27	Weight (in Kg)
28	Time period between onset to first consultation at LGBRMIMH (DUI) (in days)
29	Adhd
30	Response to medication 1 (Good/partial/no)
31	Systematic Examination (abnormal/normal)
32	Response to medication 2 (Good/partial/no)

Feature Ranking using average rank of Random Forest, Mutual Information and Pearson Correlation

Feature Ranking Results

To assess the effectiveness of our proposed ensemble method, we compared it with the individual methods. For this evaluation, we employed the Random Forest algorithm with entropy as the splitting criterion. We set the number of decision trees to 80 and considered the top 30 features for each method.

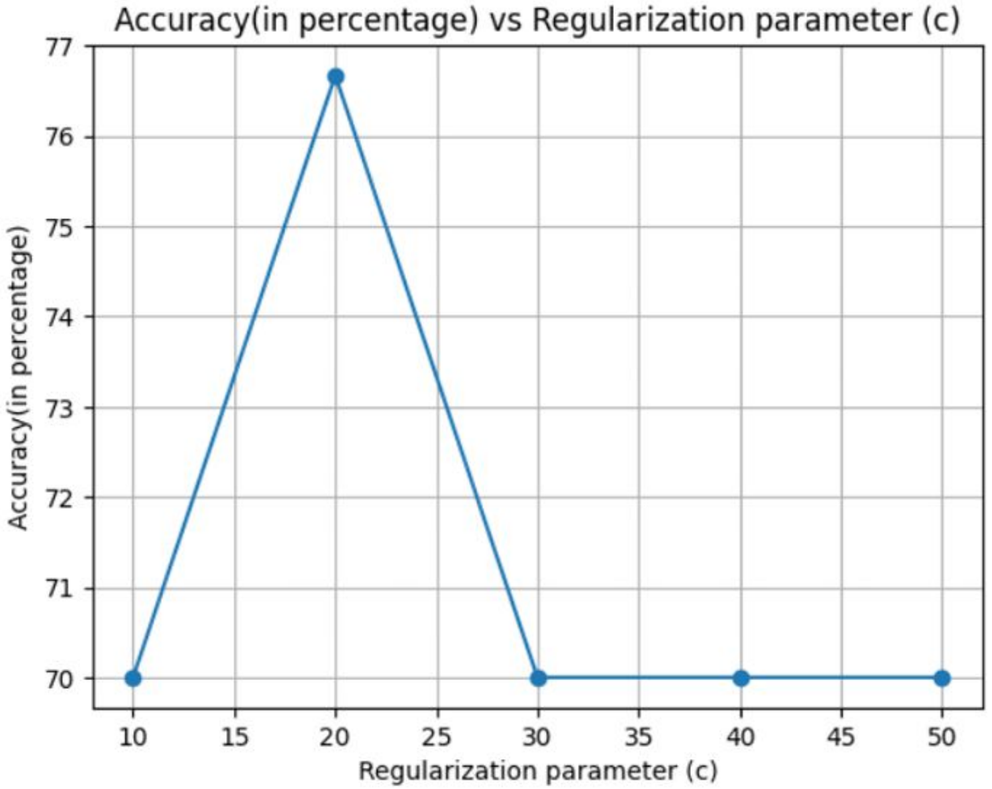
Method Used	Accuracy	Weighted Precision	Weighted Sensitivity	Weighted F1 Score
Pearson Correlation	0.800	0.812	0.800	0.802
Mutual Information	0.800	0.821	0.800	0.791
Random Forest	0.766	0.763	0.766	0.745
Ensemble Method	0.867	0.867	0.867	0.867

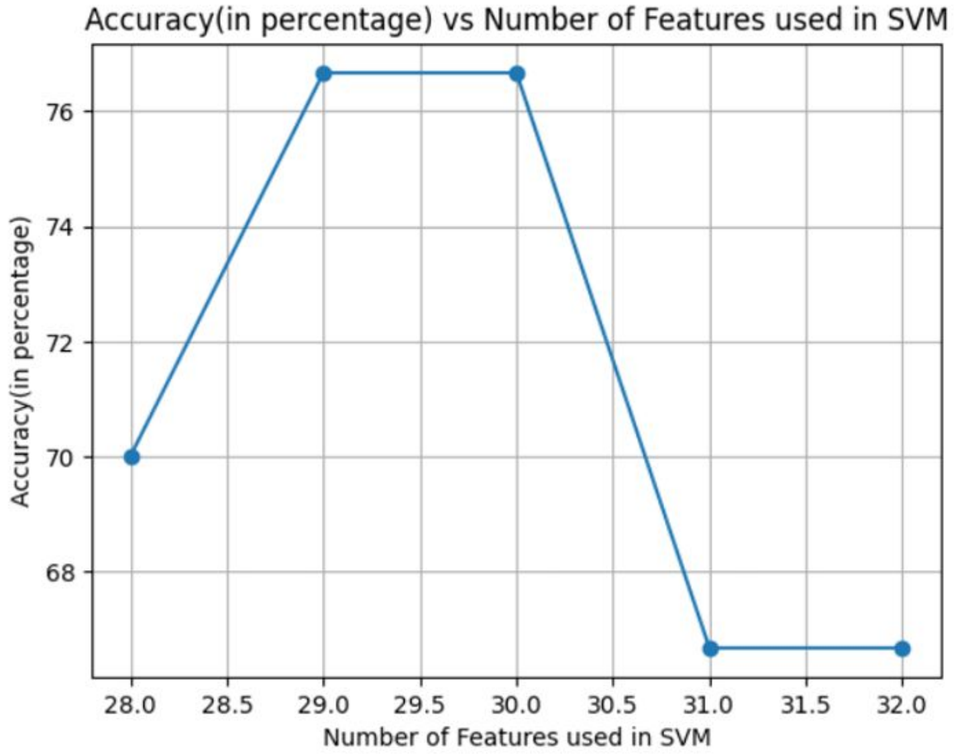
Algorithms

- SVM
- KNN
- AdaBoost
- XGBoost
- Random Forest (using entropy as splitting criterion)
- Random Forest (using weighted entropy as splitting criterion)
- Meta Random Forest (ensemble of Random Forest)

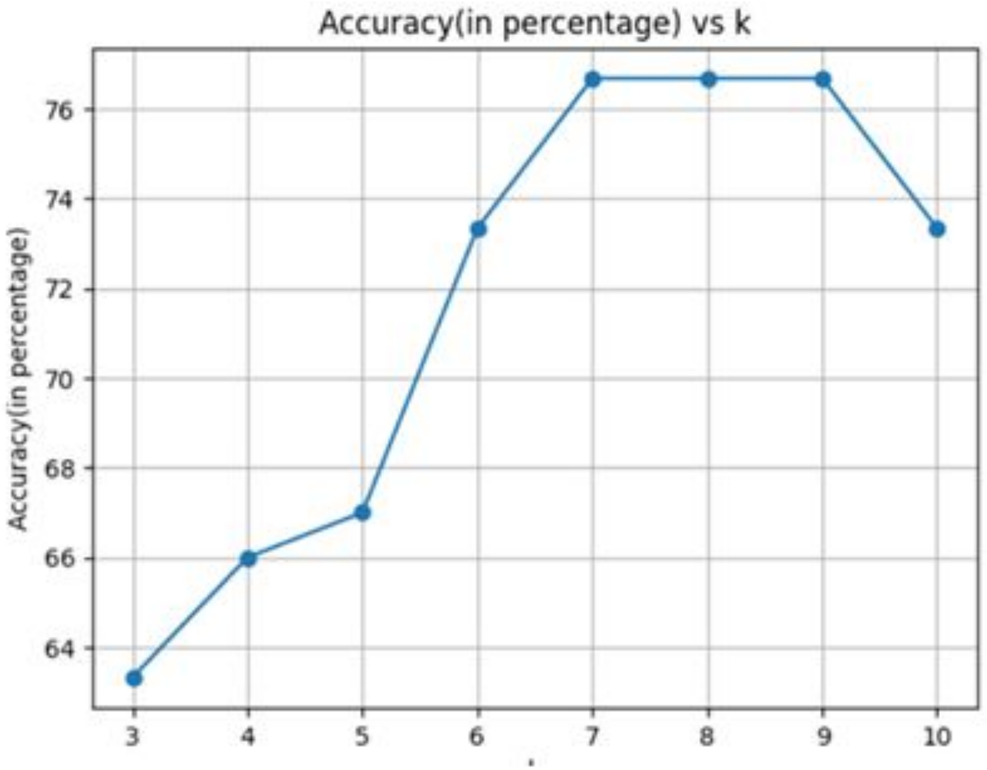
TESTING ON INITIAL DATA

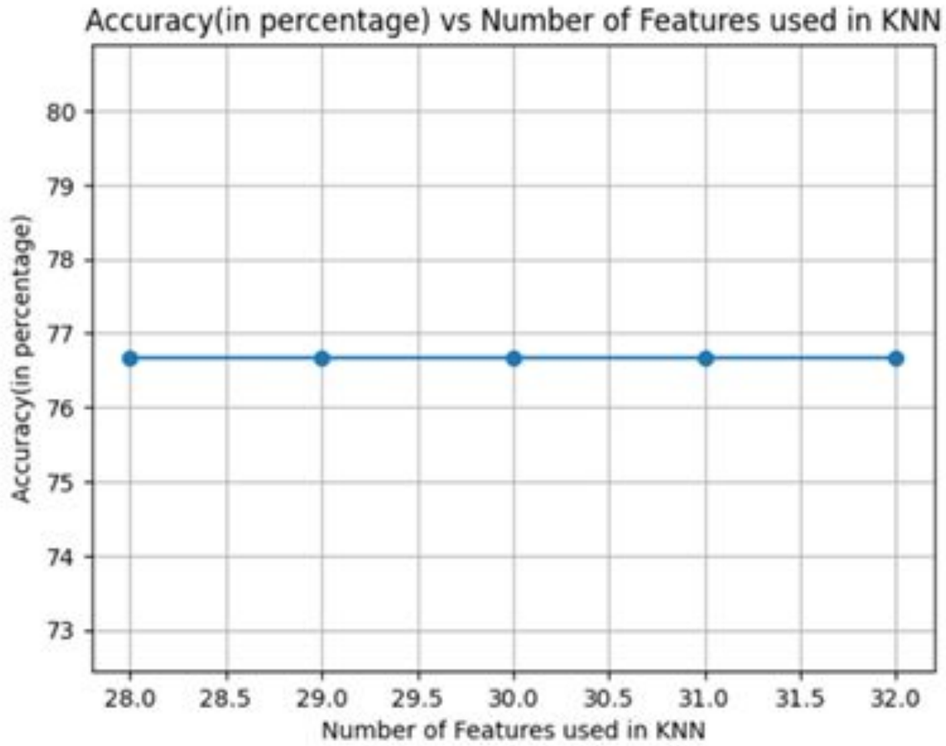
SVM


Accuracy(in percentage) vs Regularization parameter (c)
Accuracy(in percentage)
77
76
75
74
73
72
71
70
10
15
20
25
30
35
40
45
50
Regularization parameter (c)

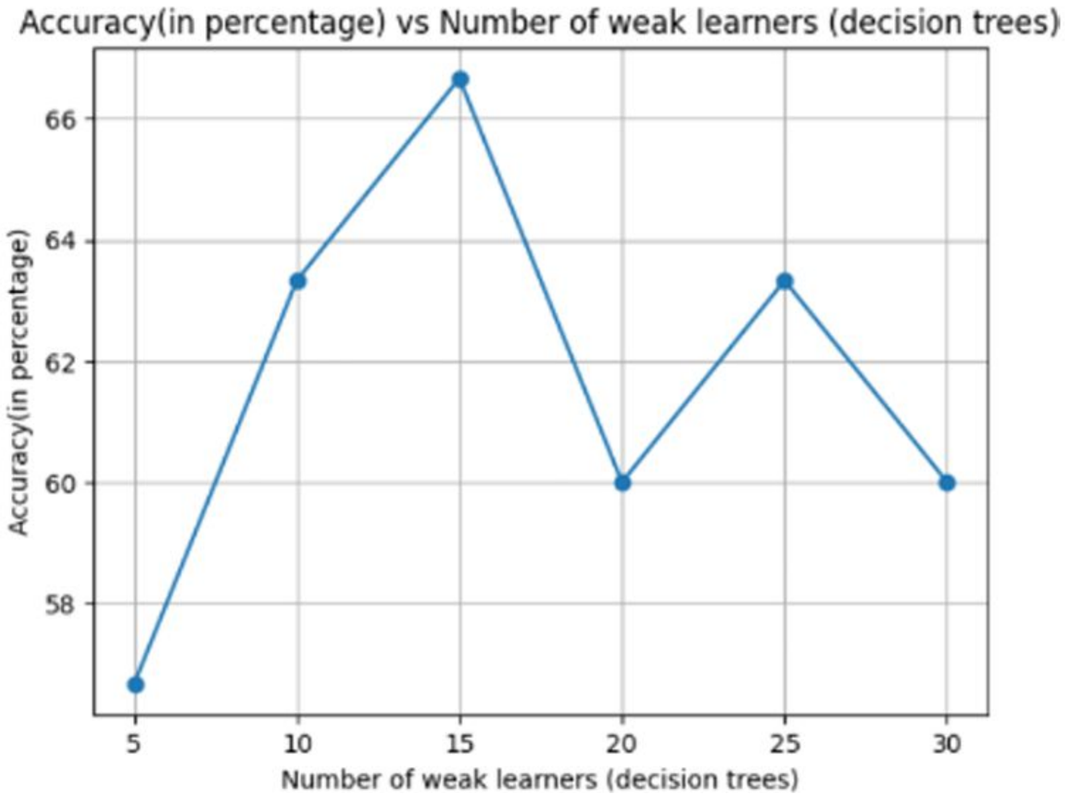

Accuracy(in percentage) vs Number of Features used in SVM
Accuracy(in percentage)
76
74
72
70
68
28.0
28.5
29.0
29.5
30.0
30.5
31.0
31.5
32.0
Number of Features used in SVM

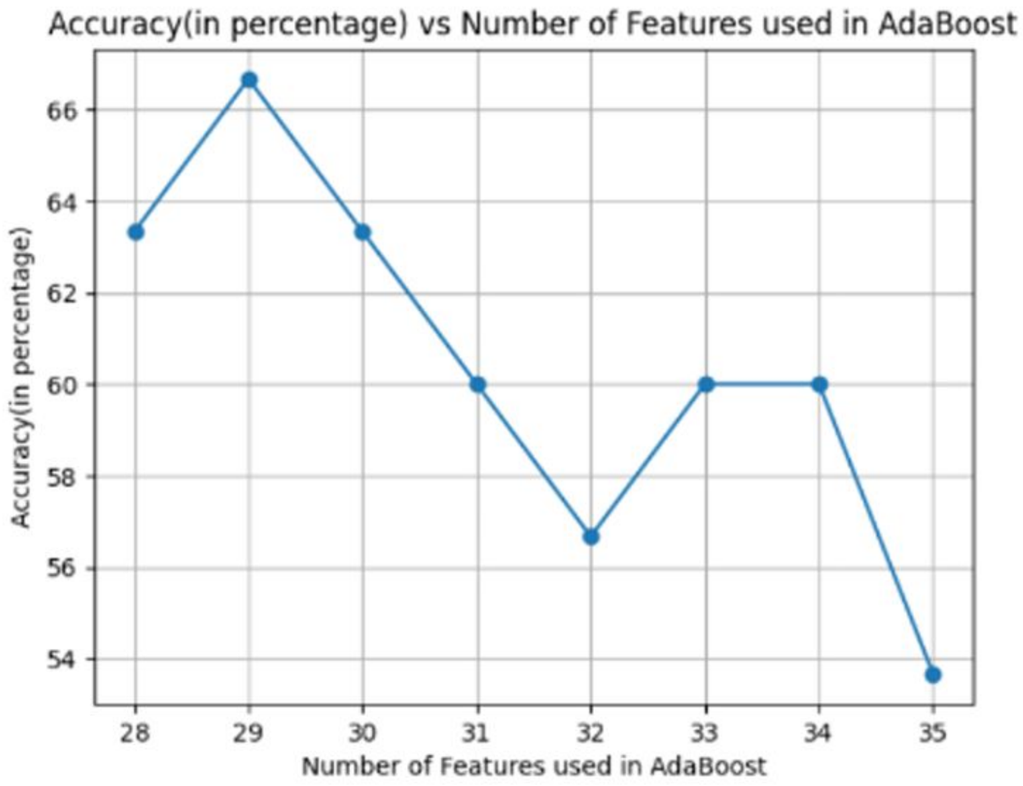
KNN


Accuracy(in percentage) vs k
Accuracy(in percentage)
64
66
68
70
72
74
76
3
4
5
6
7
8
9
10

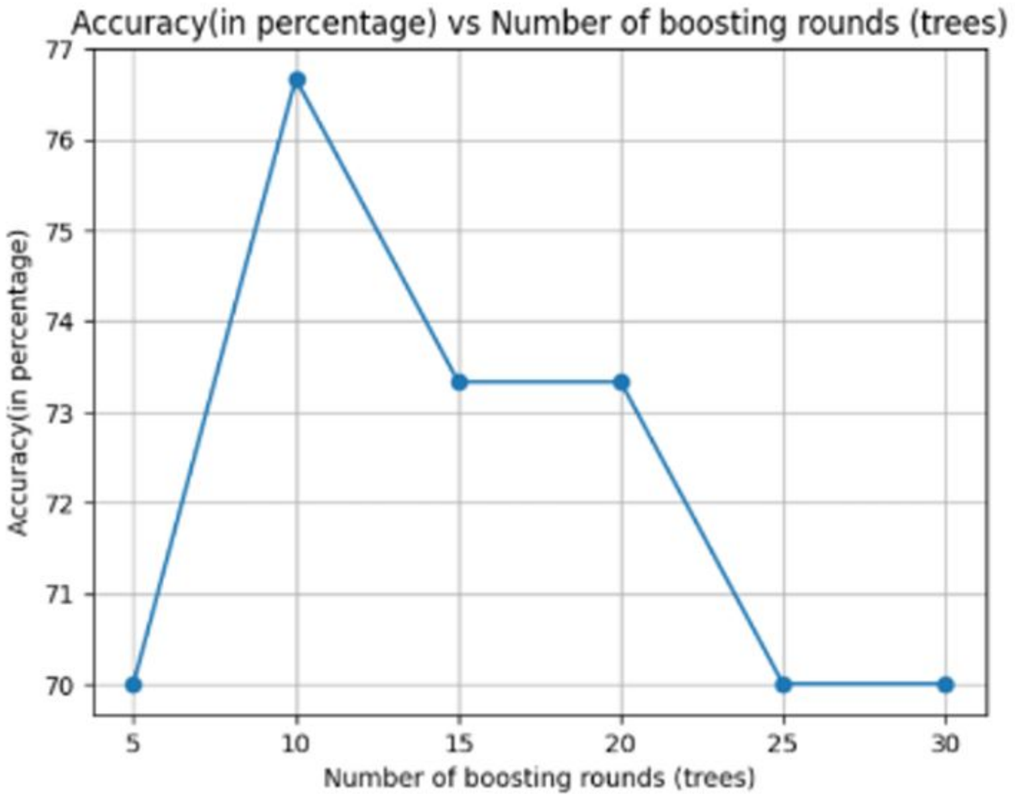

Accuracy(in percentage) vs Number of Features used in KNN
Accuracy(in percentage)
73
74
75
76
77
78
79
80
28.0
28.5
29.0
29.5
30.0
30.5
31.0
31.5
32.0
Number of Features used in KNN

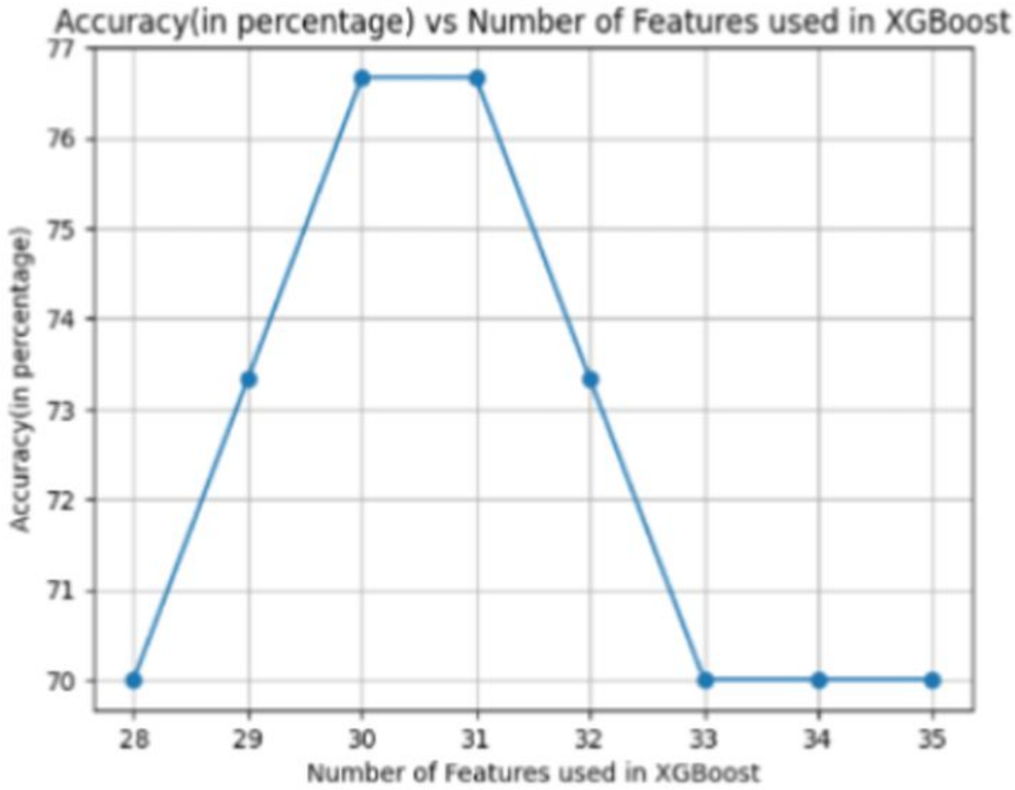
AdaBoost


Accuracy(in percentage) vs Number of weak learners (decision trees)
Accuracy(in percentage)
66
64
62
60
58
5
10
15
20
25
30
Number of weak learners (decision trees)

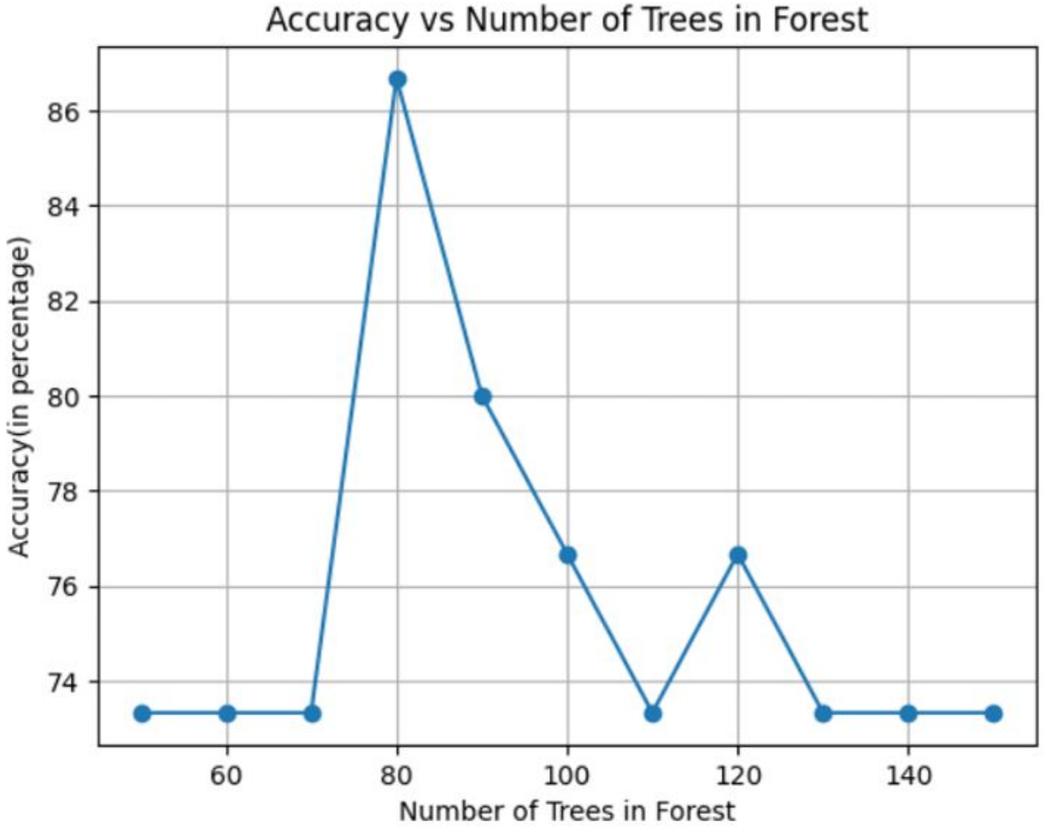

Accuracy(in percentage) vs Number of Features used in AdaBoost
Accuracy(in percentage)
66
64
62
60
58
56
54
28
29
30
31
32
33
34
35
Number of Features used in AdaBoost

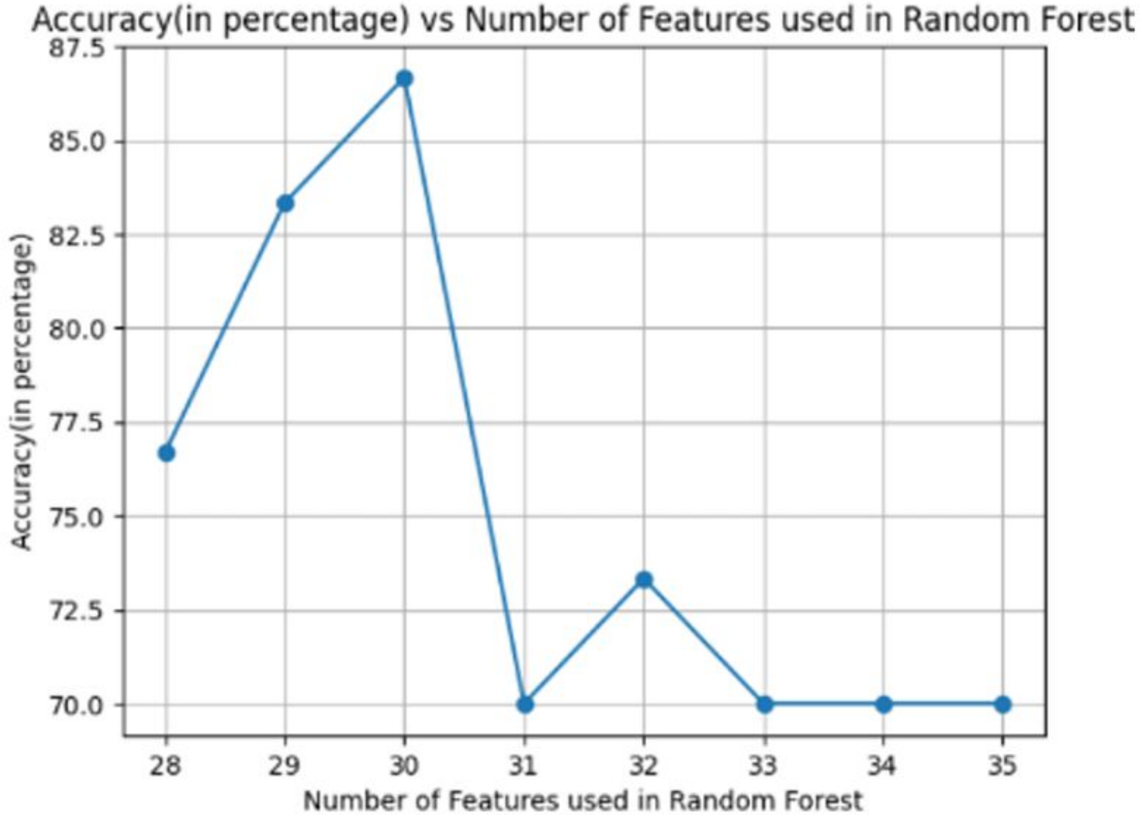
XGBoost


Accuracy(in percentage) vs Number of boosting rounds (trees)
Accuracy(in percentage)
77
76
75
74
73
72
71
70
5
10
15
20
25
30
Number of boosting rounds (trees)


Accuracy(in percentage) vs Number of Features used in XGBoost
Accuracy(in percentage)
77
76
75
74
73
72
71
70
28
29
30
31
32
33
34
35
Number of Features used in XGBoost

Random Forest (using entropy as splitting criterion)





Random Forest (using weighted entropy as splitting criterion)

Entropy: $-\sum_{i=1}^{n} p_i \log_2(p_i)$

Weighted Entropy: $-\sum_{i=1}^{n} w_i p_i \log_2(p_i)$

The information gain IG for an attribute A with weighted entropy is calculated as follows. Let S be split into subsets Sv based on the values of attribute A:

$$IG_w(S, A) = H(S) - \sum_{v \in values(A)} \frac{|S_v|}{|S|} H_w(S_v)$$

Where Values(A) is the set of all possible values for attribute A and S_v, is the subset for which attribute A has value v

Random Forest (using weighted entropy as splitting criterion)

General Formula:

- **First class weight:**

$$W_1 = \frac{1}{n} + \text{weight}$$

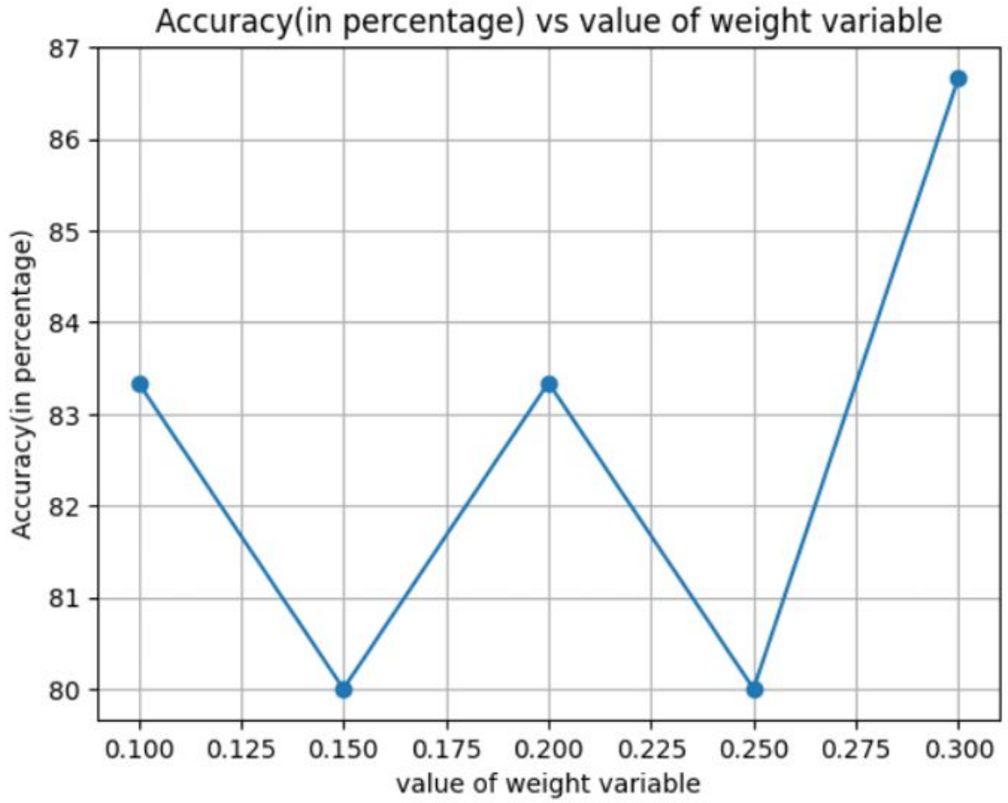
- **Second class weight:**

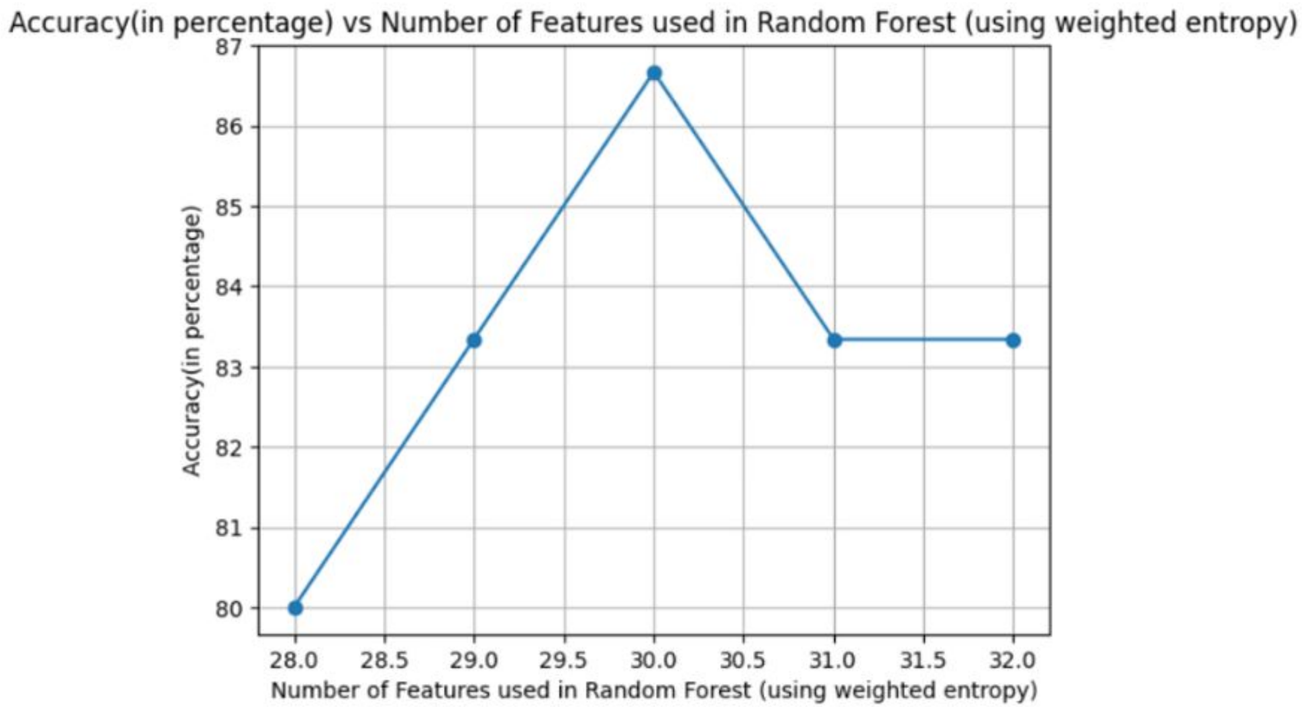
$$W_2 = \frac{1}{n}$$

- **Weights for the remaining classes:**

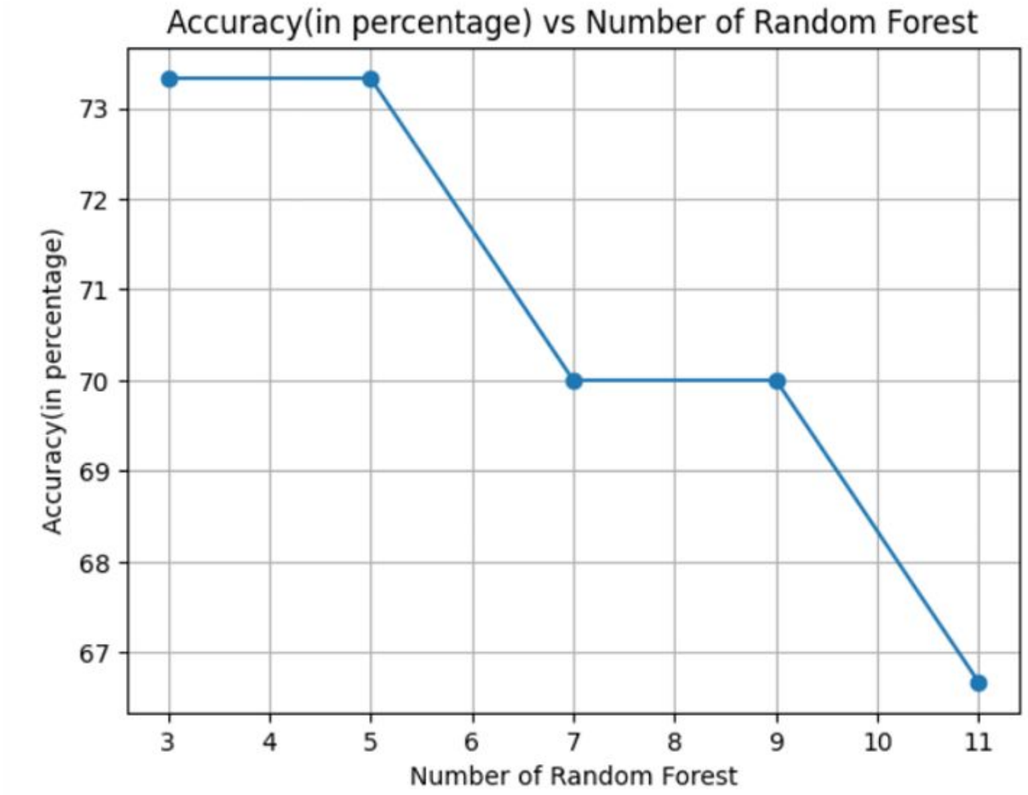
$$W_i = \frac{1}{n} - \frac{\text{weight}}{n-2} \quad \text{for } i = 3, 4, \ldots, n$$

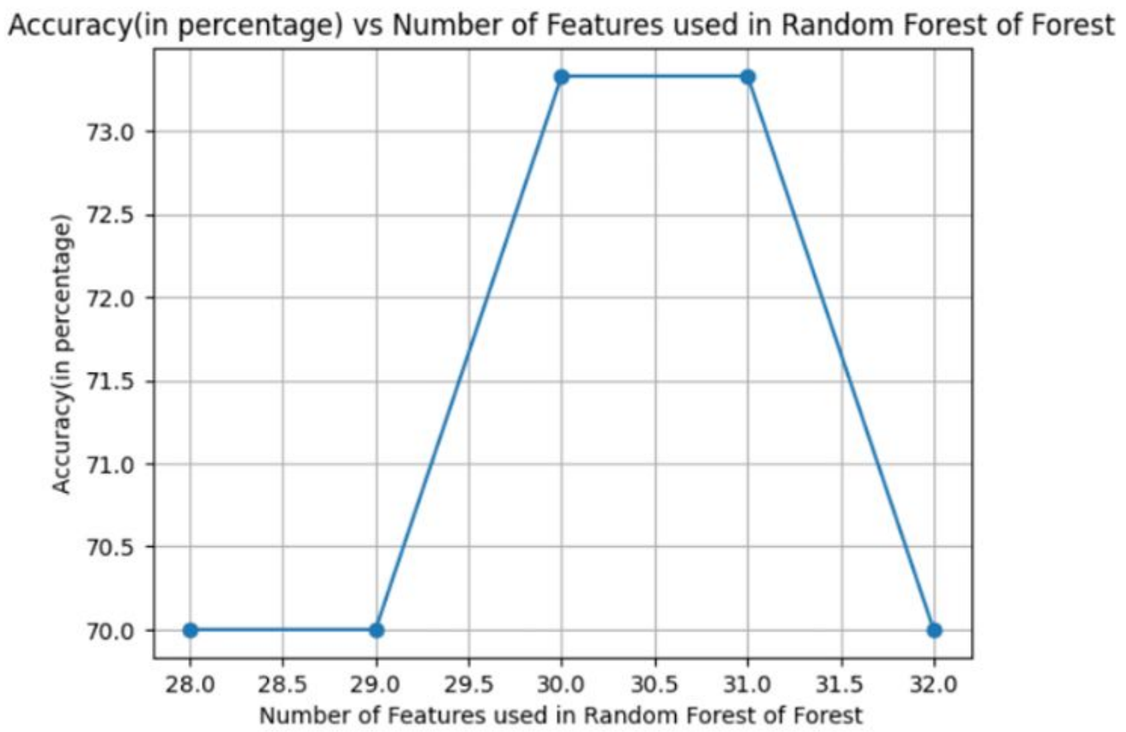
Random Forest (using weighted entropy as splitting criterion)





Meta - Random Forest





Summarized Performance of Each Algorithm

Algorithm Name	Accuracy	Weighted Precision	Weighted Sensitivity	Weighted F1 Score
Meta Random Forest	0.733	0.819	0.733	0.683
Random Forest (using entropy)	0.867	0.866	0.867	0.870
Random Forest (using weighted entropy)	0.867	0.867	0.867	0.867
AdaBoost	0.689	0.715	0.689	0.691
XGBoost	0.767	0.779	0.767	0.764
SVM	0.767	0.803	0.767	0.753
KNN	0.767	0.826	0.767	0.781

EXPLAINABLE AI

Explainable AI (XAI) refers to techniques and methods used to make artificial intelligence (AI) models more interpretable and understandable to humans.

DEFINITION

Explainable AI (XAI) addresses the challenge posed by black-box AI models, providing insights into how AI systems arrive at their decisions. This transparency enhances trust, accountability, and regulatory compliance.

IMPORTANCE

Explainable AI (XAI) techniques include model inspection, feature importance analysis, and explanation methods. These approaches enable users to understand the factors influencing AI model predictions and decisions.

TECHNIQUES

EXPLAINABLE AI

LIME

LIME is an interpretability technique that explains individual predictions of machine learning models. It works by perturbing the input data around a specific instance and observing the changes in predictions, thus approximating the model locally with an interpretable model

SHAP

SHAP sees all possible combinations of features and their impact on predictions, thus revealing which features exert the most influence on model outcomes

EXPLAINABLE AI FEATURE RANKING

Rank	Feature Name	Average Probabilities
1	jerky	0.004883
2	School Adjustment	0.004398
3	total frequency	0.004219
4	total number of follow up at LGBRIMH	0.004089
5	systemic examination (abnormal/normal)	0.003870
6	eye contact	0.003600
7	Follow up diagnosis changed or not (yes/no)	0.002786
8	depressed	0.002619
9	Mental status examination/Behavioral Observations	0.001802
10	significant psychosocial stressor	0.001609
11	Distance from LGBRIMH (in KM)	0.001529
12	Max Duration of resolution of symptoms before recurrence/relapse (in days)	0.001496
13	Continued medication 1/stopped/changed	0.001306
14	Socioeconomic status	0.001198
15	Age at last follow up	0.001066
16	mean gap ratio at lgb (total no of months of follow-up divided by no of follow-ups)	0.000968
17	Rural/Urban	0.000760
18	Medication possession ratios 1(MPRs) in lgb;x-syrup	0.000605
19	maximum period of compliance at lgb (in days) (longest streak of good compliance)	0.000489
20	Religion	0.000389
21	irritable	0.000373
22	Avg dose of medication 1 (Mode value of medication)	0.000145
23	seizure	0.000120
24	Time period between onset to first consultation	-0.000072
25	Academic performance	-0.000141
26	Age at presentation (in yrs)	-0.000170
27	Number of In patient cares	-0.000274
28	Total duration of medication 2 (in days)	-0.000320
29	poor	-0.000371
30	Response to medication 2 (Good/partial/no)	-0.000431
31	Medication possession ratios 2(MPRs) in lgb	-0.000671
32	Age at onset(in years)	-0.000733

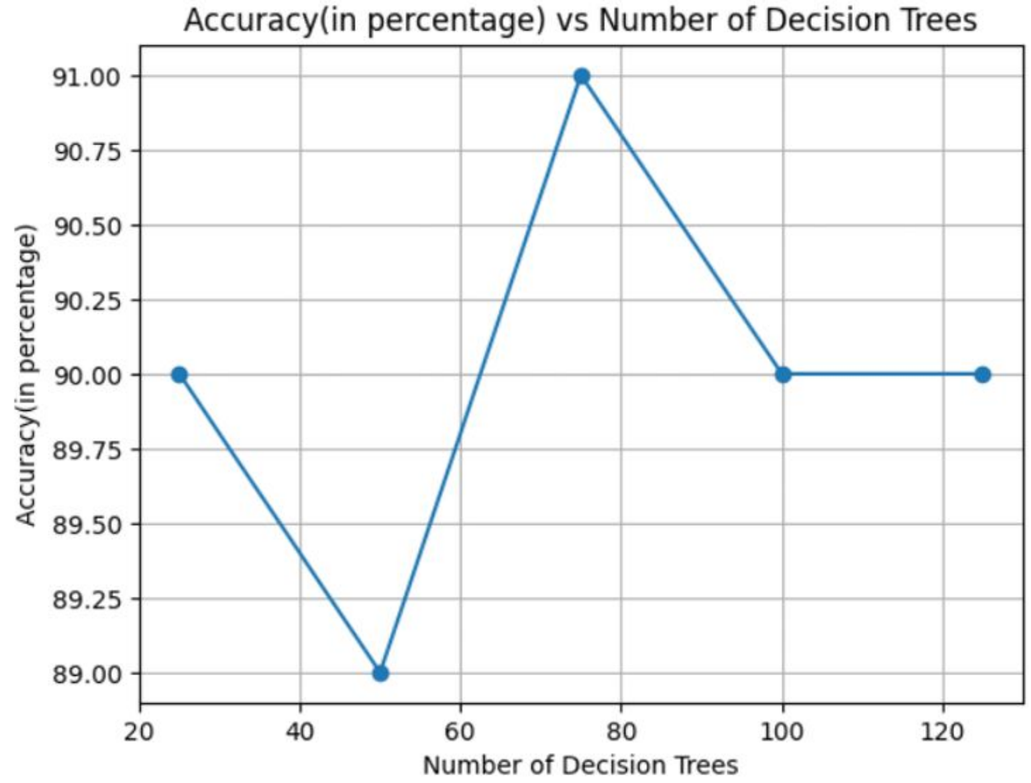
LIME FEATURE RANKING

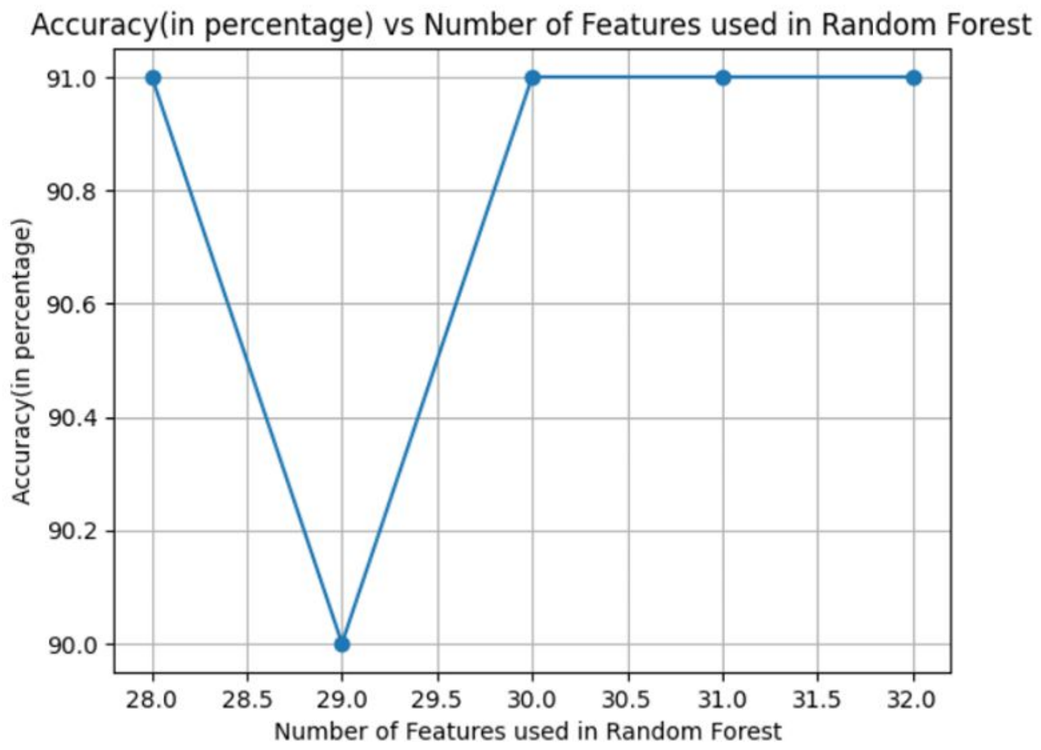
Rank	Label Name	Average Importance
1	Off-medications duration (to add all such durations over follow-up in days)	0.032107
2	total number of follow up at LGBRIMH	0.028937
3	maximum period of compliance at lgb (in days) (longest streak of good compliance)	0.024616
4	total_frequency	0.024439
5	days/freq	0.017878
6	Maximum duration of symptom free period (in days)	0.017711
7	Medication possession ratios 1(MPRs) in lgb	0.012903
8	School Adjustment	0.012857
9	No of relapses/exacerbations	0.012759
10	Continued medication 2/stopped/changed	0.011886
11	Max Duration of resolution of symptoms before recurrence/relapse (in days)	0.011326
12	Age at presentation (in yrs)	0.011321
13	Age at last follow up	0.010211
14	total_days1	0.009757
15	total duration of medication treatment at LGB(in days) (from first consultation to last follow-up)	0.008405
16	mean gap ratio at lgb (total no of months of follow-up divided by no of follow-ups)	0.008319
17	weight (in Kg)	0.007885
18	restless	0.007397
19	Total duration of medication 2(in days)	0.007348
20	adhd	0.007080
21	Response to medication 1 (Good/partial/no)	0.007025
22	Total duration of medication 1 (in days)	0.006820
23	Medication possession ratios 2(MPRs) in lgb;x-syrup	0.006715
24	Distance from LGBRIMH (in KM)	0.006207
25	Socioeconomic status	0.005854
26	Continued medication 1/stopped/changed	0.005535
27	Time period between onset to first consultation at LGBRIMH (DUI) (in days)	0.004776
28	Academic performance	0.004539
29	Maximum dose of medication 1 (in mg)	0.004465
30	Avg dose of medication 1 (Mode value of medication) (in mg)	0.004210
31	Age at onset(in years)	0.004056
32	Angry	0.004029

SHAP FEATURE RANKING

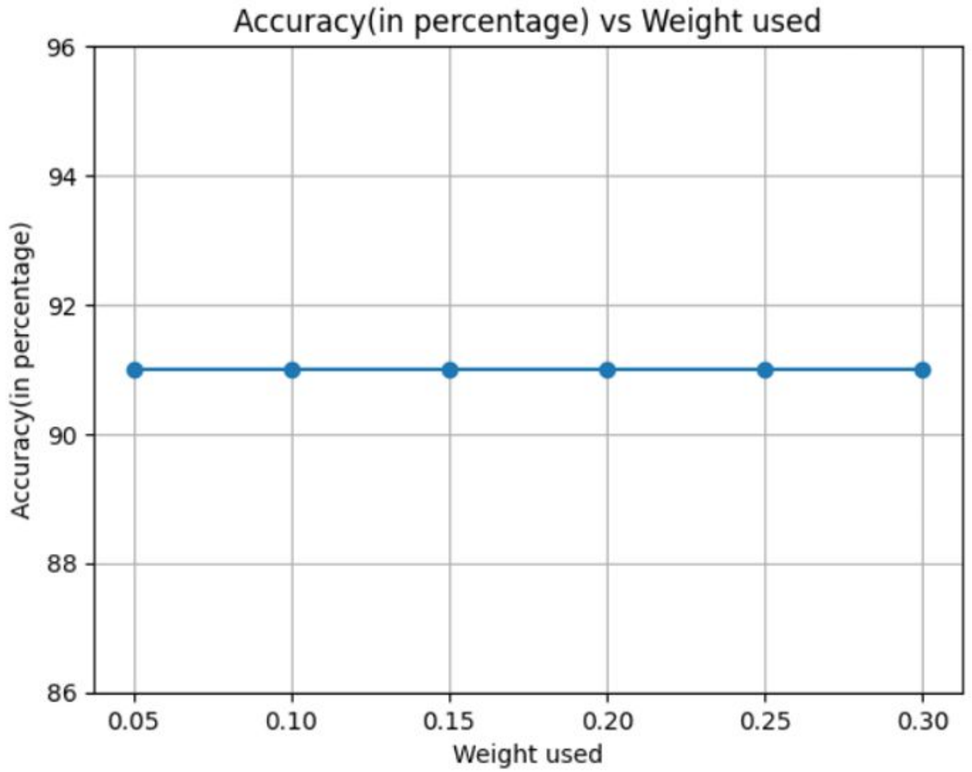
TESTING ON FINAL DATA

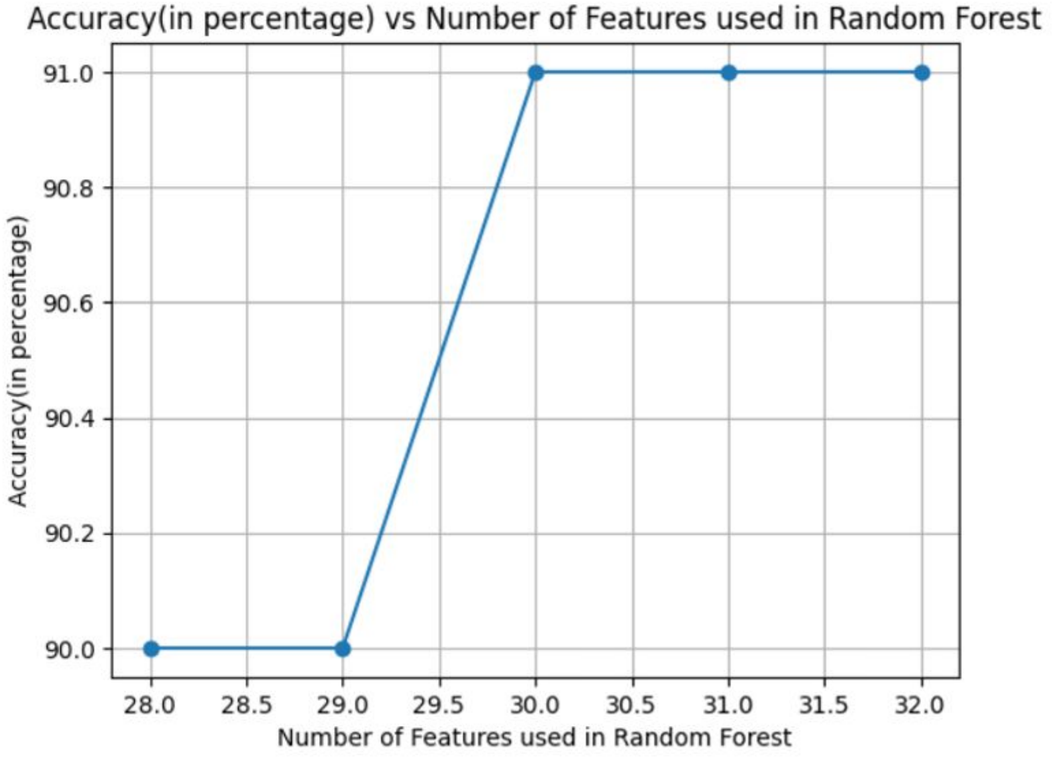
Random Forest (using entropy as splitting criterion)



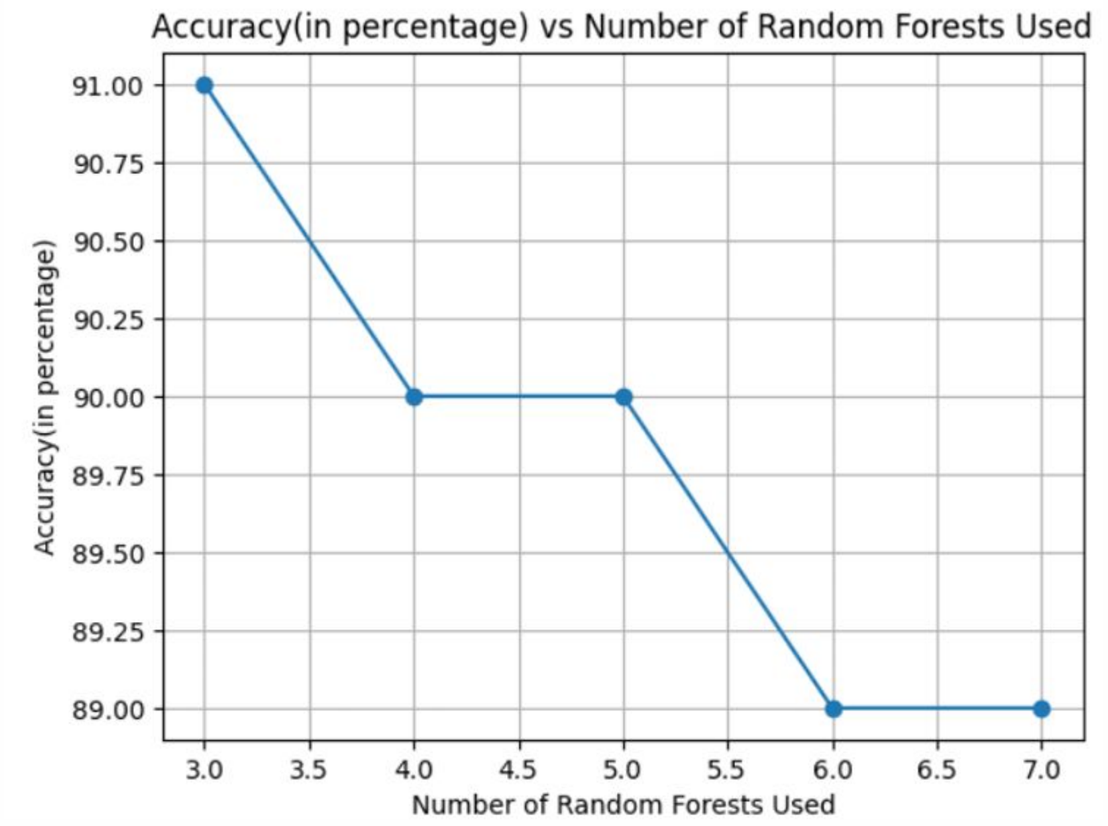


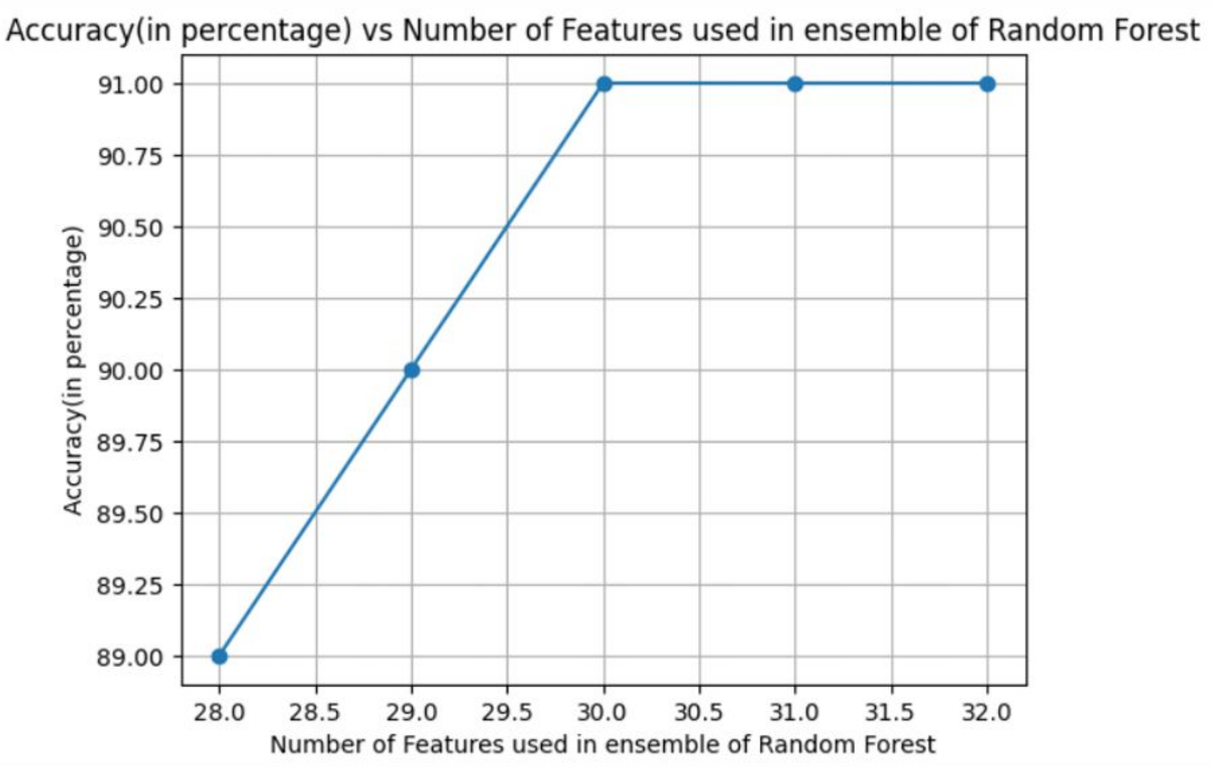
Random Forest (using weighted entropy as splitting criterion)





Meta Random Forest





Summarized Performance of Each Algorithm

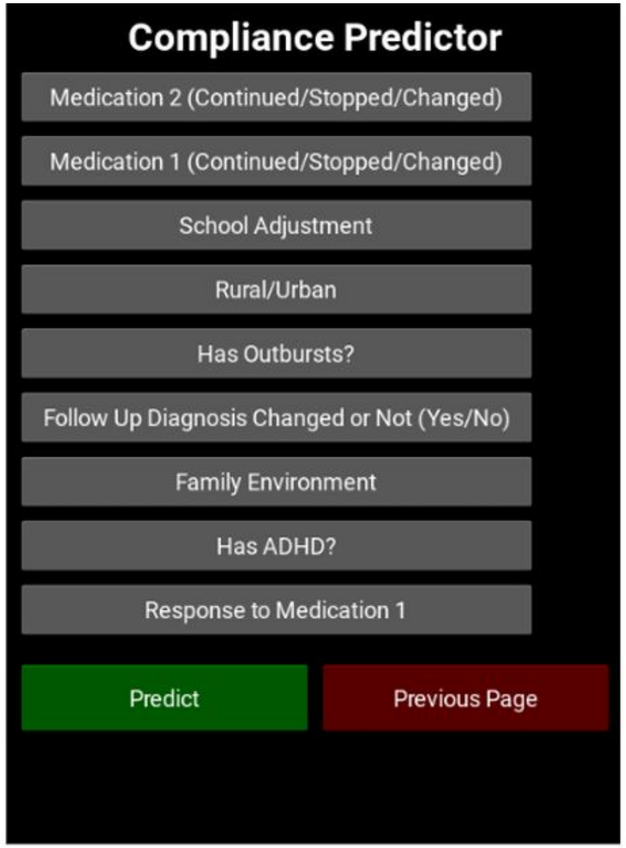
Algorithm Name	Accuracy	Weighted Precision	Weighted Sensitivity	Weighted F1 Score
Meta Random Forest	0.906	0.888	0.906	0.891
Random Forest (using entropy)	0.906	0.909	0.906	0.891
Random Forest (using weighted entropy)	0.906	0.857	0.906	0.880

Application Building

i) Language Used: Python

ii) Package Used: Pandas, NumPy, Scikit-learn, Joblib, Kivy

iii)Software Used: VSCode

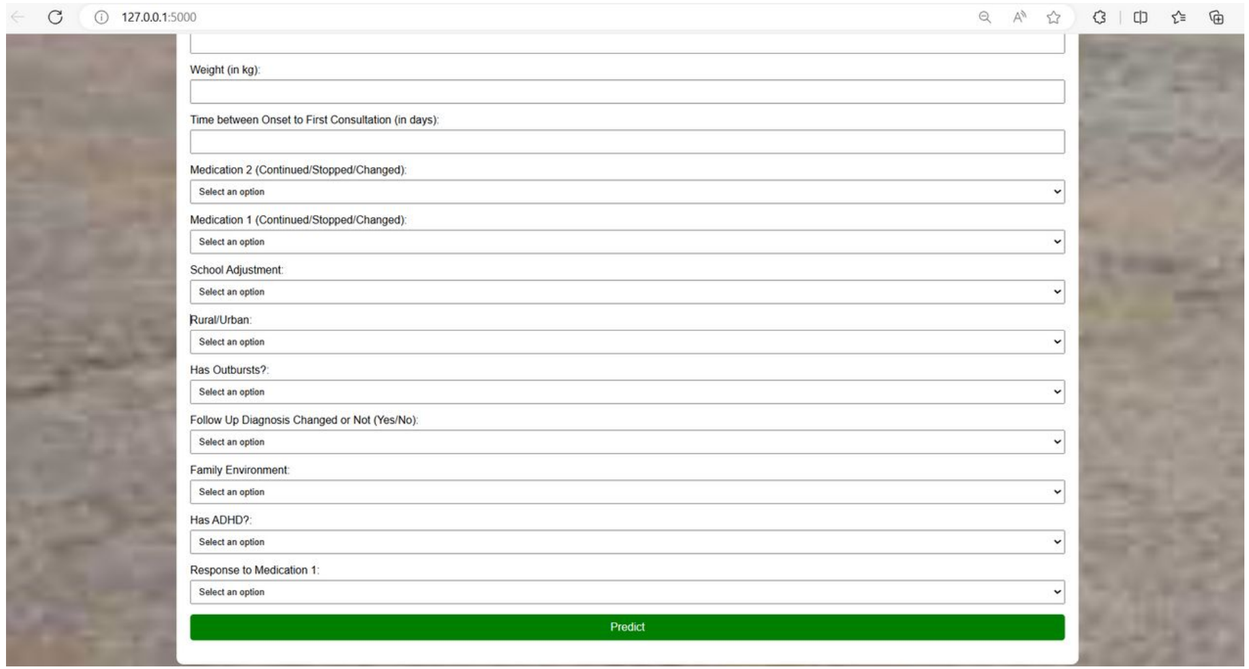


Web Tool Building

i) Language Used: Python, HTML, CSS

ii) Package Used: NumPy, Scikit-learn, Pickle, Flask, Pandas

iii)Software Used: Jupyter Notebook, VSCode



Conclusion

- Our study investigated the performance of various supervised learning algorithms on real data, focusing on accuracy and other evaluation metrics.
- We found that using an ensemble of Pearson Correlation, Mutual Information, and Random Forest (RF) for feature ranking was superior to individual methods.
- RF achieved the highest accuracy of 90.68% with entropy splitting, 330 training and 140 testing patient data, 75 decision trees, and the top 30 features.
- Our weighted entropy approach in RF also yielded optimal accuracy.
- These findings highlight the importance of algorithm selection, parameter tuning, and feature selection in predictive performance, validating the top 30 features obtained in our feature ranking as clinically accepted and most important.

Future Works

- Launch our application on mobile devices.
- Host our webtool on website.
- Inclusion of more data.
- Propose methods to reduce the dependence on the feature ranking obtained the LIME and SHAP methods, and give more importance to our feature rank, which was clinically validated.

Publications

- One Research paper has been accepted and published.

Talukdar, D., Sarmah, R., Siddeswara, B. L., Bharadwaj, C., Subramani, G., Kulkarni, N., & Yube, M, Predicting Poor Compliance to Psychotropics using Machine Learning Approach, 4th International Conference on Machine Learning and Big Data Analytics(ICMLBDA) 2024, National Institute of Technology Kurukshetra, India, 2024, NIT kurukshetra, (Springer).

- Another journal paper is still being written for the “International Journal of Clinical Pharmacy” (Springer).

THANK YOU