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Predicting Household Savings Behaviour for Financial Sustainability: Leveraging Machine Learning to Foster Economic Resilience

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Abstract:-
Household Saving Behaviour is the base for Financial Sustainability that promotes long-term development and economic resilience. According to the Indian context, the ancient book "Arthashastra" stresses the management of resources, advocating both saving and acquisition of money as a moral and practical goal. It also stresses careful financial management, promoting the allocation of revenue for various family activities. The ancient Tamil scripture "Thirukkural" emphasizes saving as a road to manage resources wisely, supports the notion of financial resilience that leads to sustainable progress. This research tries to connect ancient concepts with new technology techniques by predicting household Saving Behaviour using different machine learning algorithms. To predict Saving Behaviour, several characteristics such as demographic and socio-economic, cultural, and civilization aspects have been incorporated to build the best-fit model. Advanced ML models such as Support Vector Machine, Gradient Boosting Classifier, Random Forest Classifier, and Naïve Bayes and others are used to predict Saving behaviour. Evaluation of each model is done using several measures such as accuracy scores, precision, recall and F1 – score to find the best-fit model. By comparing the accuracy ratings of each model, the most accurate model to predict Saving behaviour is selected.

Keywords: Financial Sustainability, Predictive Analytics, Machine Learning, Household Savings, Ancient Scriptures

Introduction:

Financial uncertainty is among the most critical economic resilience drivers that allow individuals, families, and nations to ride through financial hardship to long-term prosperity. Saving behaviour of the household is a categorical determinant of economic stability since it affects investment patterns, financial security, and overall economic development. With increased economic threats, inflationary climates, and unforeseen downturns on the rise, comprehension and expectation of financial uncertainty are essential today than ever before. Comprehension of how to forecast saving behaviour is important for policymakers, banks, and citizens in order to chart economic choices towards long-term financial prosperity. The spirit of prudent management of money and saving is ingrained in Indian epistemological tradition. The ancient treatise, Kautilya's Arthashastra, is a classic book on statecraft, war, and economics with sage advice on management of resources, frugality, and sound fiscal policy (Rangarajan, 1992). It practices shrewd budgetary restraint, wise spending, and wise deployment of funds for the long-term economic health. Likewise, Thirukkural, the ancient Tamil work by Thiruvalluvar, seriously considers thrift and fiscal sense as first maxims to run assets (Parthasarathy, 2009). Consistent with the scripture, prosperity, if complemented with prudence and individual self-control, guarantees personal security, as well as local society prosperity. The ancient literature portrays saving as a core activity to balance fiscal weaknesses and facilitate fair economic development.

Ancient Indian philosophy recognizes that saving at home is not just an act of withholding wealth but a deliberate instrument of economic living. The Vedic texts also stress fiscal discipline, appealing to people to follow a balanced approach towards earning, spending, and saving (Sharma, 2011) . Manusmriti guides the earning of wealth in an ethical way, wise expenditure of it, and keeping some amount for future uncertainties. Rigveda and Atharvaveda mention the habit of thrift and right financial behavior (Apte, 2008). These fall directly into practice of economic resilience today, wherein money saved under tight control contributes to societal stability and personal economic independence. However, even though such economic maxims from the past are extremely valuable, they alone lack predictive value to keep up with the requirements of the current economy's complexity. Conventional ways of saving, as great as they are theoretically, will most likely fail to forecast dominant trends in the current economy, especially in a world of volatile foreign markets, unreliable inflation rates, and technological disturbances. This deficiency calls for the integration of traditional economic expertise and contemporary computational tools—primarily, machine learning (ML)—with the vision of enhancing economic prediction and choice-making (Chakraborty, 2017).

Machine learning (ML), a subdiscipline of artificial intelligence (AI), is a sophisticated computational tool to investigate dynamic patterns in finance, find relations, and generate predictive approximations. ML methods can be applied to research household saving behavior through examination of large databases taking into account socio-economic, demographic, cultural, and civilizational factors (Jordan, 2015) . The algorithms possess sound ability to examine various financial parameters, such as the level of income, employment rates, inflation trends, monetary consciousness, social norms, and policies of the government. By statistical learning and pattern detection, ML-based models outperform traditional statistical models in detecting subtle patterns that may otherwise be overlooked. The ability of ML to predict is not only useful in simple prediction, but it can be used for having an impact on real-world financial decisions at the microeconomic and macroeconomic levels. At the household level, proper saving behavior forecasting enables households to make optimal financial choices, maximizing investment and consumption. At the country level, higher household savings translate to higher capital formation, faster investment growth, and higher economic stability (Bhatia, 2019) . Saving is a cushion against finance shocks because it lowers the vulnerability of economies to slowdowns and stimulates long-term growth.

Additionally, ML-based predictive financial analytics will revolutionize finance decision-making. As fintech becomes more popular and there is an abundance of more data, the use of ML in predicting will make economics more resilient, promote frugal savings, and increase money wisdom (Aggarwal, 2018). Policymakers are able to take advantage of such forward-looking forecasting analyses while making forward-looking financial policies, steer clear of economic disproportions, and promote domestic economic stability. Apart from being technology and policy-relevant, the study is also intended to reaffirm the evergreen relevance of Indian maxims to finance. The basic principles of moderation in saving, outlined in works such as the Arthashastra, Thirukkural, and Manusmriti, are very comfortably accommodated within modern predictive analytics, and thus validate the virtue of frugal saving to protect one's assets. By combining machine learning with this ancient insight, the research provides us with an economic alternative that is practical but remains faithful to the spirit of mainstream economic theory. Finally, this combination of ancient financial concepts and cutting-edge AI-based analytics alone can create a stable and equitable financial future.

By using predictive modelling to enhance saving forecasting, consumers and institutions make more informed financial choices, minimize economic inequality, and improve financial access. This cross-disciplinary methodology places the long-term value of saving at the center as the key to economic resilience, being faithful to the eternal principle that wise stewardship of finances is the way to sustainable prosperity.

Literature Review:

Prudence is explained in centuries-old ancient books, Kautilya's Arthashastra explains economic concepts with precedence given to saving, investing, and money-making for wealth in the future (Rangarajan, 1992) . Thirukural, another Tamil ancient literature by Thiruvalluvar, similarly says one needs to be careful and stingy in financial things, explaining how thrift brings firmness and strength during times of uncertainty (Balasubramanian, 2009). These writings prove that saving for the future and planning finances are vital aspects of economic resilience, virtues still valid in the modern day. The modern finance system is far removed from concepts found in ancient texts. Keynesian economics, for instance, gives great importance to savings in the progress of economies and phases of business cycles (Keynes, 1936). Modigliani-Brumberg life-cycle theory is a description of how an individual allocates resources over a lifetime (Modigliani, 1954) . Behavioural finance is critical of traditional assumptions regarding rationality and also takes into account the role of psychology in investment and savings decision-making (Thaler, 2004). Advances in the use of technology in finance have also influenced saving behaviour, with the introduction of the mobile bank and automatic save devices making saving more accessible (Ozili, 2018) . Household savings play an important role in bringing stability to the economy and individuals' safety. It can be seen that family savings are primarily driven by income, financial literacy, and social issues primarily responsible for household saving behaviour (Lusardi, 2014) . Household saving behaviour is also affected by the economic policy and banking systems, and research has proven that access to banks promotes the saving rate (Beck, 2007). Also, cultural variations play a very strong role in savings behaviour by region (Carroll C. D., 2019) . Psychological, social, and economic factors can be analyzed to determine savings behaviour. The Theory of Planned Behaviour posits that attitudes, subjective norms, and perceived control influence savings decisions (Ajzen, 1991). Evidence based on empirical studies indicates that interventions in financial education enhance saving behaviour (Bernheim, 2001) . Moreover, recent work indicates the contribution of digital financial services towards stimulating savings behaviour for households (Dupas, 2013) . Gender-based differences in making financial choices also affect saving behaviour at the household level (Croson, 2009). Individual financial well-being and macroeconomic stability are covered by financial sustainability. Sustainable financial behaviour renders economies and individuals resilient to shocks. Research indicates that saving is instrumental to long-run economic resilience and financial stability (Carroll C. D., 1997) . Institutions and governments play an important role as well in bringing about financial sustainability through saving- and investing-fostering policies (Claessens, 2007) . Interventions for financial literacy have been found to enhance financial sustainability outcomes (Atkinson, 2012) . Machine learning has been instrumental in forecasting financial behavior. Decision trees, neural networks, and regression analysis have been used to examine savings behavior from demographic and economic information (Xiao, 2017). Machine learning models were found to provide better prediction of financial values by identifying financial patterns within individual financial records (Gupta, 2021) . Big data and AI implementation strengthens dynamic estimation of saving action more strongly (Huang, 2020). Recent developments with deep learning technique strengthen forecasting of financial activities further towards personalized recommendation of finances (Brown, 2021) . Despite so large amount of literature specific to savings behaviour, few studies synthesize conventional finance knowledge with ongoing financial sustainability techniques appear surprisingly limited. Although existing literature explains practices of machine learning and behavioural finance in financial prediction, a lack of application of economic ideas of previous times in religious texts like Arthashastra and Thirukural in the forecasting framework could be seen. This paper aims to bridge this gap by integrating prior economic dogma knowledge with present AI-based savings prediction models.

Methodology:

Research Design

This study utilizes quantitative research design for analysing and predicting household savings behaviour. This research aims to develop predictive models which helps in providing insights into financial sustainability by integrating traditional wisdom form ancient Indian scriptures with modern machine learning techniques.

Data Collection

This study focuses on the household savings across various regions of India and the regions were arrived from Forbes report (2024) for selecting the top 10 states in India contributing to GDP. This study also focused in rural, semi-urban and urban households of all the selected states. To ensure representation from various income groups, family structure and educational backgrounds multi-stage stratified sampling was used. Data was collected from 2637 individuals to gains insights on their savings behaviour.

Data preprocessing

Handling Missing Values: Imputation techniques were used to handle missing values. Mean or Median imputation was applied to replace missing values for numerical features such as income and expenditure. Mode imputation was utilized for categorical features such as occupation and education.

Normalization & Standardization: To ensure all features are equally contributing to model training, numerical features were standardized by using z-score normalization (normalization by mean subtraction and division by standard deviation). Min-max scaling was also attempted to normalize all feature values to the [0,1] range.

Encoding Categorical Variables: The categorical variables were represented in numerical form. One-hot encoding was applied to nominal categories such as type of employment and level of education, while label encoding was applied to ordinal variables such as income levels.

Splitting the dataset: The dataset was split into the training (80%) and testing (20%) in order to assess the performance of models

Tools Used

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Tool used in this paper is Jupyter notebook. Jupyter notebook is a type of application that is available online to create and run codes, equations, texts and visualizations. This tool helps in doing Exploratory data analysis, check accuracy scores with the help of different machine learning approaches and evaluates the model by various metrics in order to rely upon it.

Evaluation Metrics

Accuracy Score estimates the general accuracy of a model by computing the ratio of household saving behaviours correctly predicted to all predictions but can be deceptive in unbalanced datasets. Precision suggests the percentage of true savers among all predicted savers, with fewer false positives, while Recall estimates the number of actual savers that were correctly predicted, minimizing false negatives. F1-score is the harmonic mean between Precision and Recall, balancing both in a way that will give a better measure of model performance in the case of imbalanced household savings data.

Results:

A. Support Vector Machine

Table 1. Evaluation Metrics of SVM

Accuracy Score	0.96	
Precision	0.96	0.97
Recall	0.97	0.95
F1	0.97	0.96

In Predicting household savings behaviour, high accuracy has been demonstrated by the Support Vector Machine (SVM) model. The accuracy for classifying savers is 97%, depicting the model is very reliable in classifying those who save. Recall for non-savers is 97%, shows the model identifies most non-savers correctly. The F1-score, a trade-off between precision and recall, is 96-97%, which points to high robustness. This implies that SVM is a good classifier of households according to savings behaviour and is a good predictive instrument. Minor misclassifications, however, imply that external economic and psychological variables sometimes affect savings patterns in an unpredictable manner.

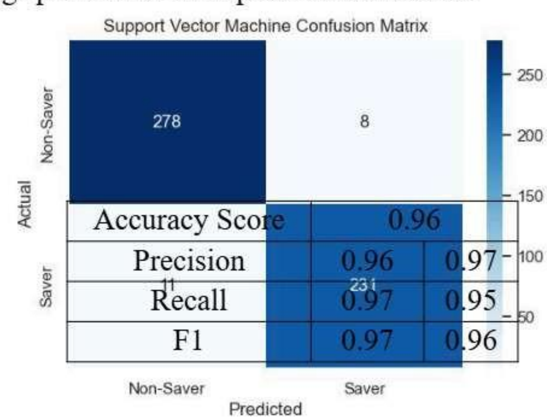


Fig 1. Confusion Matric of Support Vector Machine

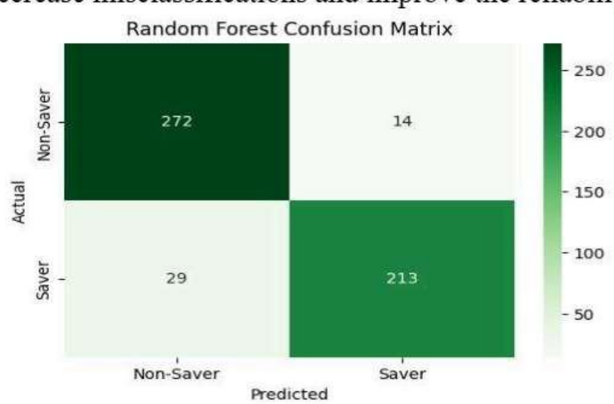
The Support Vector Machine (SVM) model classifies household saving behaviour with a very high precision of 96%. Its confusion matrix accounts for its precision on classification by correctly classifying 278 of the non-savers and 231 of the savers. Yet, it incorrectly classified 8 non-savers as savers, potentially picking up financial volatility in behaviour, and 11 savers as non-savers, potentially picking up unstable saving behaviour or unobservable items such as financial literacy and investment behaviour. From a modern finance perspective, the findings are consistent with economic theory in modeling saving behaviour in terms of income security, consumption behaviour, and overall economic state. The high precision and recall rates of the model are also an indicator of its stability. From a philosophical perspective of ancient texts, nevertheless, saving is not only an economic activity but a religious and ethical obligation as well that falls under social conventions, family obligations, and moral codes. The misclassifications may be an indication of deeper, non-monetary reasons, including religious principle on keeping money or socially inspired financial conduct. For example, the potential of saving by some families through concealed channels through gold or social channels is not recorded under standard financial reports. Additionally, religious scriptures preach the wealth circular behaviour tendency of balance, as opposed to gathering the surplus, and could be one cause for stating the reasons why, with high income levels, there are certain families that do not display major tendencies of saving. The significance of this is that no matter how sophisticated machine learning tools such as SVM are, incorporating behavioural, psychological, and sociocultural determinants—i.e., the ones derived from experience centuries ago will make predictability feasible.

B. Random Forest Classifier

Table 2. Evaluation Metrics of RFC

Accuracy Score	0.92	
Precision	0.90	0.94
Recall	0.95	0.88
F1	0.93	0.91

Random Forest model obtains an accuracy of 92%, showing high but marginally lower predictive capability than SVM. The precision for the savers is 94%, that is, the model effectively identifies the savings households. The recall for the non-savers is 95%, depicting most non-savers are correctly identified. Yet, the recall for the savers is 88% shows that there are misclassifications of the savers. The 93% F1-score of non-savers and 91% F1-score of savers reflect well-balanced performance, yet the model tends to perform less effectively in classifying all saving households. This reflects that although Random Forest works well, there is potential to decrease misclassifications and improve the reliability of prediction.



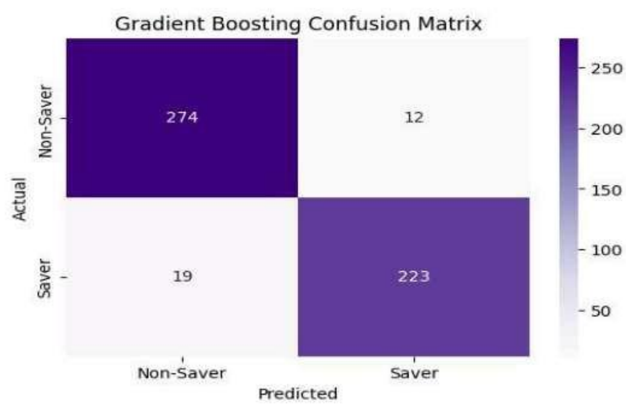
This indicates information regarding the reliability of the Random Forest model in making predictions on saving behaviour by households. The model correctly classifies 272 non-savers and 213 savers, which is overall reliability. The model misclassifies 14 non-savers as savers, something that could be caused by the unique instances of one-time cash receipts or peculiar consumption behaviour that imitates saving patterns. Second, 29 of the so-called "non-savers" are misclassified, and likely most of them are non-formal saving vehicles like gold accumulation or unreported saving not captured in official statistics. From a contemporary finance point of view, the misclassifications are proof of the limitation of data-dependent techniques in capturing the nuances of financial behaviour. Decisions to save depend on a large number of variables such as liquidity preference, degree of financial sophistication, and investment policy. The comparatively low recall value of 88% for savers indicates that there are some exotic unconventional or non-standard saving families that are being mis-classed. Classification errors are delegated to more influential sociocultural determinants of saving behaviour by early scripture. Saving is acquired as money habit and a moral duty in prudence values, dharma (duty), and long-term family happiness. These families are able to save outside institutional arrangements outside the model. This would imply that the cultural and behavioural nature of machine learning algorithms is influencing their accuracy in predictability.

C. Gradient Boosting Classifier

Table 3. Evaluation Metrics of GBC

Accuracy Score	0.94	
Precision	0.94	0.95
Recall	0.96	0.92
F1	0.95	0.94

Gradient Boosting model has 94% accuracy, high prediction ability in saving behaviour classification of households. Precision for saving households is 95%, or the model strongly discriminates saving households with very few false positives. Non-savers' recall is 96%, so most of the non-saving households are identified correctly. Recall on savings households is lower at 92%, meaning some saving households are incorrectly predicted. 95% of the F1-score for the non-savers and 94% for savers show balanced as well as sound performance from the model. Generally, Gradient Boosting is a strong predicting agent, with the possibility that slight improvements might augment saver prediction.



The confusion matrix reveals the accuracy of the Gradient Boosting model in classifying household savings behaviour. The model accurately identifies 274 non-savers and 223 savers, with high accuracy. But 12 non-savers are incorrectly identified as savers, which could be indicative of periodic or seasonal savings practices that the model mistakenly interprets as a

Journal of Informatics Education and Research
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Vol 5 Issue 3 (2025)

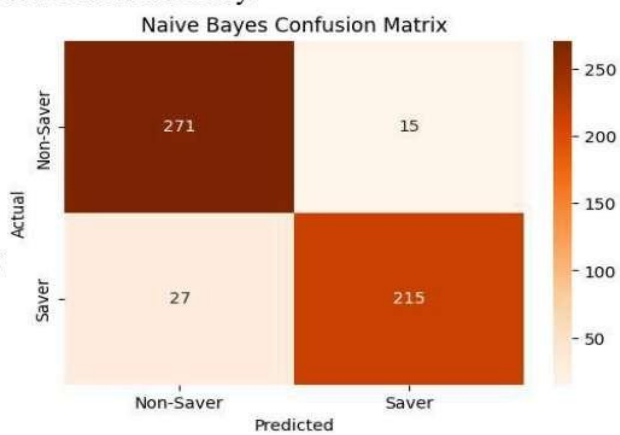
saving trend. There are also 19 wrongly identified savers as non-savers, which could be as a result of irregular saving practices, implicit savings methods, or economic hardships not reflected in the data. From a contemporary finance point of view, the findings support the theory that saving behaviour is explained by several economic factors including financial stability, knowledge about finance, and availability of financial instruments. The high performance of the model demonstrates that machine learning methods are able to learn structured financial behaviour efficiently, albeit difficulties in extracting unstructured patterns of saving behaviour. From an ancient scriptures point of view, the misclassifications are due to the general idea of wealth preservation that goes beyond mere savings. According to traditional doctrines, savings not only mean financial accumulation but moral and social obligations, and traditionally this is undertaken through other than monetary means such as investment in land, village savings, or gold storage. Households shaped by these doctrines might not neatly fall into traditional financial categories, so their savings behaviour is more difficult to anticipate. This implies that the inclusion of behavioural, psychological, and cultural factors in machine learning models would improve predictive power.

D. Gaussian Naïve Bayes (GNB)

Table 4. Evaluation Metrics of GNB

Accuracy Score	0.92	
Precision	0.91	0.93
Recall	0.95	0.89
F1	0.93	0.91

The Naïve Bayes model has a 92% accuracy, showing the model has good predictive power in classifying household saving behaviour. Precision for savers is 93%, and the model does a good job of identifying people who save. Recall for non-savers is 95%, and most of the non-savers are correctly classified. The recall for savers is slightly weaker at 89%, and some of the savers are being misclassified as non-savers. The 93% F1-scores (non-savers) and 91% (savers) indicate an even performance, though the model is not able to entirely ascertain all saving households. Improving feature selection and using behavioural dimensions can potentially enhance classification accuracy.



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Confusion matrix enables us to evaluate the performance of Naïve Bayes model in classifying savings behaviour of households. The model can classify 271 non-savers and 215 savers accurately, which proves its reliability. In contrast, 15 non-savers were incorrectly labeled as

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 3 (2025)

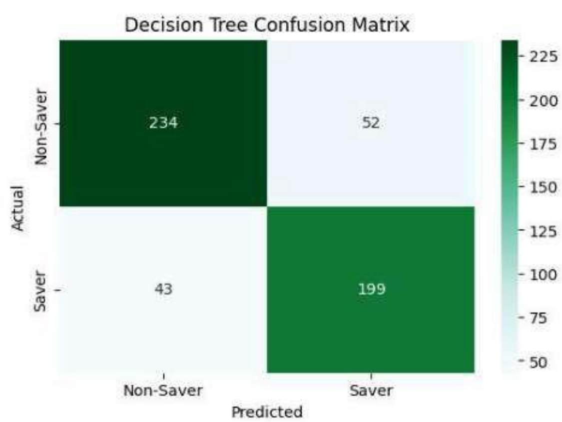
savers, suggesting overestimation of saving inclination due to unbalanced financial behaviours. Other than that, there are 27 people who are mistakenly classified as non-savers, suggesting a few households keep some informal methods of saving or save with in-regularized patterns the model does not catch. From a modern finance perspective, such results are consistent with economic theory under which saving behaviour is influenced by the amount of disposable income, spending habits, and access to financial resources. The model's low misclassification of savers can be attributed to the challenge of distinguishing between discretionary spending and actual saving behaviour as well as variability in financial restraint. From a point of view of ancient scriptures, misclassifications can occur through the broader cultural and philosophical bases of saving. Ancient wisdom views savings as not merely a financial act but a responsibility in terms of long-term family welfare, religious fulfillment, and social contribution. Certain families can be engaged with the goal of maintaining wealth in non-monetary forms, such as land, gold, or social wealth, not captured by traditional financial models. This serves to highlight the need to incorporate qualitative variables like cultural norms and savings attitudes into predictive models. The discipline could then integrate machine learning with traditional finance wisdom to create a more holistic conceptual framework for household savings behaviour.

E. Decision Tree

Table 5. Evaluation Metrics of DT

Accuracy Score	0.82	
Precision	0.84	0.79
Recall	0.82	0.82
F1	0.83	0.81

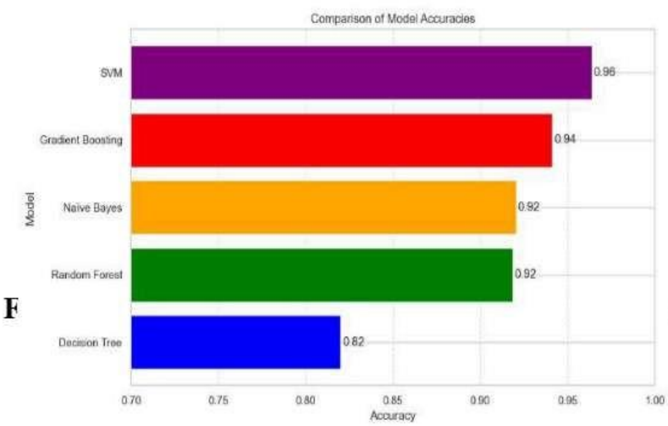
The accuracy of the Decision Tree model is 82%, showing moderate effectiveness in predicting household savings behaviour. Its precision for savers is 79%, indicating a greater rate of false positives compared to other models. The recall of non-savers and savers is both 82%, which indicates that the model correctly identifies an equal percentage of both but is not specific about separating them. The 83% F1-score (non-savers) and 81% F1-score (savers) tell us that the model is not bad, but incorrectly classifies a vast majority of households. This calls for optimization, either through ensemble methods or by the addition of additional behavioural variables.



Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 3 (2025)

Confusion matrix reveals the Decision Tree model's propensity to classify in forecasting household saving behaviour. It correctly classifies 234 non-savers and 199 savers but misclassifies 52 non-savers as savers and 43 savers as non-savers. The large number of false positives (52) indicates that the model is likely to be overestimating saving tendency in households with uncertain income or unaffordable financial discipline. Likewise, the 43 false negatives suggest that there are some true savers who are not picked up, perhaps through non-traditional or non-cash saving habits. Lower accuracy and precision of the Decision Tree according to the modern finance perspective imply that savings conduct is not absolutely dichotomous and needs a stronger financial profiling. Those who save or invest only in the so-called alternative assets such as property or precious metals could be incorrectly classified through model specification. Moderate performance suggests also that non-complicated rules of decision can capture efficiently the sophisticated financial activities and economic differences. Based on scriptures of old perspective, traditional prudence perceives saving as a duty entailing good living and existence in the long term. Certain families, according to religion or communal economies, might not be part of regular saving forms and hence contribute towards model inaccuracies. Ambiguity of the model supports the integration of behavioural and philosophical aspects within economic prediction. More recent methods might be more accurate by adding previous financial data, cultural values, and qualitative factors to machine learning models to arrive at a comprehensive model of household saving behaviour.

F. Bar Chart of Predictive Models



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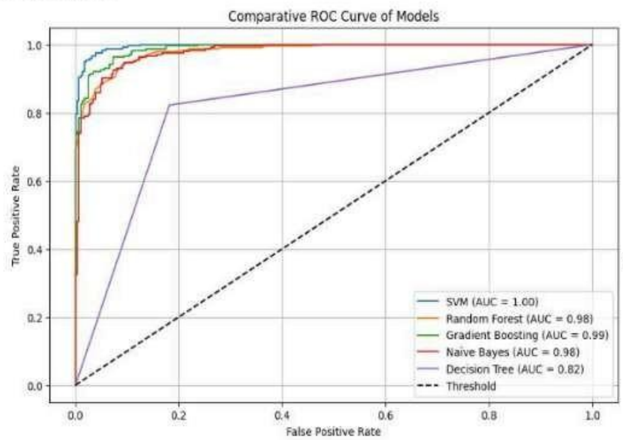
Ranking the models according to accuracy provides an exact impression of which machine learning model is more predictable in terms of predicting savings behaviour of households. Support Vector Machine (SVM) occupies the top rank with maximum accuracy of 96% by being capable of classifying the savers and non-savers effectively. Gradient Boosting stands second best at 94% accuracy by proving its effectiveness in classifying the advanced savings behaviour through stepwise improvement of misclassifications. Naïve Bayes and Random Forest models are highly predictable at 92%, which is extremely high predictability but slightly offset by assumption in data and feature importance variance. The lowest accuracy of 82% from the Decision Tree model also indicates that simpler decision rules might not be sufficient to capture the complexity of family financial behaviour. From a contemporary finance viewpoint, more accurate models such as SVM and Gradient Boosting indicate that saving choices are regulated by a system of variables that are interdependent such as stability of income, finance literacy, and consumption patterns. Machine learning enables analysis of such variables at a deeper level through accurate categorizations that can be used to guide financial planning action. From a classical scripture view, saving is not only a financially rational decision but one of moral and social responsibility according to cultural convention and long-term sustainability. The low performance of the Decision Tree model means that straightforward classifications are potentially ignoring such deeper drivers, but that more advanced models such as SVM and Gradient Boosting might more easily be able to handle heterogeneous behavioural drivers. It is therefore possible, through combining machine learning and conventional financial insight, to develop an integrated model for prediction and inducing long-term family saving behaviour.

G. Comparative ROC curve



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ROC curve analysis displays the performance of different machine learning algorithms in comparing the prediction of family savings behaviour. AUC values show that SVM is the best as it distinguishes between savers and non-savers most accurately. Gradient Boosting, Random Forest and Naïve Bayes are highly predictive, i.e., the three models are highly effective in distinguishing between the two groups. The least performer is the Decision Tree model meaning that it is of low effectiveness in dealing with intricate decision boundaries for savings behaviour classification. As per the modern economic perspective, the results highlight that savings conduct is governed by different determinants such as income stability, consumption conduct, and financial consciousness.

Conclusion:

This study fills the gap between ancient Indian monetary thought and contemporary machine learning techniques in predicting family saving behaviour, rising economic resilience, and budgetary solvency. Ancient wisdom as reflected in texts like the Arthashastra and Thirukkural has always focused on saving frugality and money management as a means to achieve the ultimate stability. Their philosophy is consistent with modern economics theory, reaffirming the fact that frugal saving builds economic strength at both the individual and national level. The classical financial management approaches are, however, not sufficient enough to address the complexities of modern economies and the use of high-end predictive analytics is thus necessitated. With the support of machine learning algorithms, this study precisely estimates the saving behaviour according to demographic, economic, and behaviour variables. From the study, it is evident that SVM performs better than other models with a rate of 96% accuracy and thus the best classifier for household savings prediction. Lastly, this research proposes that financial sustainability is a temporal concept where past knowledge must be sharpened by current computational systems to optimize decision-making. Combining antiquated financial wisdom with sophisticated computational systems is an integrative way of constructing and comprehending household saving behaviour.

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