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Development of AI-Based Financial Planning Tools for Small Businesses

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ABSTRACT

Access to expert advice on financial planning is a limitation for small businesses because of little access and the dynamic economy. This research presents the creation of an AI based financial planning tool designed for the micro enterprises. At the proposed methodology, I use a structured machine learning pipeline to improve the decision making and forecasting of financials. Across different financial indicators of small businesses, the dataset is submitted through rigorous data transformation techniques, normalization, and log scaling to handle skewed distributions and ensure feature comparability. It improves efficiency of the model as well as its interpretability by removing unnecessary variables and selecting the relevant ones with filter methods like Pearson correlation. This is implemented as an SVM model in classification tasks such as risk assessment and financial behavior prediction. The tool performs very well in finding and extracting critical financial patterns and creating actionable insights. By giving small businesses an intelligent, affordable planning solution, this research helps them engage in better financial health and sustainability in the face of competitive market environment.

Keywords: *Artificial intelligence, financial planning, small businesses, machine learning, SVM classification, data preprocessing, feature selection.*

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1. INTRODUCTION

Financial planning is an important aspect of their running and growing small businesses. But with limited resources, a lack of financial expertise and very unsteady market conditions, most of the small enterprises find it difficult to make sound financial decisions. As the power of AI and MLcontinues to grow, there is a vast opportunity to come up with intelligent tools that can provide the help to small businesses when it comes to financial forecasting, budgeting and risk assessment [1]. The research presented here is an aid of an AI based financial planning tool for helping small businesses with their niche requirements.To classify financial behavior and evaluate financial health, the proposed model utilises Support Vector Machine a powerful supervised learning algorithm among others. In order to make model accurate and relevant for our model, we do a lot of massive data preprocessing like normalization, log transformation and many more [2]. Standardization of features and managing the skewed distributions of financial data are essential these steps to avoid skewed distributions of financial data and give optimal performance on the model [3].

Reduction in dimensionality is possible and also model interpretability is improved through feature selection. The very important filter used to eliminate the features in the dataset that are not significant they are rather filtered using the filter method which is Pearson correlation. This method improves computational efficiency and guarantees that what the model attends to are variables with maximum predictive power [4].

Integrating these methods in a unified framework, the developed AI based tool gives practical insights, based on the data, to small business owners. This helps users to assess how they stand financially, check what risks they might fall victim to, and make better strategic decisions. Not only does this research serve as a strong contribution to the field of financial technology, but it also tends to a real-life malaise by making intelligent financial planning accessible to small-scale enterprises. Overall, we seek to enable small businesses with cheap and person friendly AI solutions to boost financial stability and also facilitate long term growth.AI in Financial Planning for Small Businessesshown in figure 1.

Figure 1.AI in Financial Planning for Small Businesses

Figure 1 image brought to life by this visual is titled 'AI in Financial Planning for Small Businesses' and demonstrates four functions through which AI can help small business financial management. This includes Financial Forecasting, where artificial intelligence predicts forecasted financial trends and performance for fair planning; Budgeting Assistance, allowing for building and handling budget more efficiently; Risk Assessment based on the potential threat to the financial future; and Strategic Decision-Making using data to make decisions as per the need of the business to grow [5]. The functions are color coded and being linked to a central hub powered by AI to showcase a span of integration and centrality of AI in altering financial operations for small businesses.

2. RELATED W ORK

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have found their way into financial planning, though mostly for small businesses which lack a connection to a qualified financial planner. AI has potential to automate and optimize all the financial decision-making processes with numerous studies to show such.Patel and Shah (2021) considered data transformation techniques, such as normalization and standardization, in the context of the application of data transformation techniques to improve accuracy on the predictive models with respect to the small business financial analysis. Finally, their work confirmed that preprocessing financial data is very important for making models perform better, especially for dealing with skewed distributions [6].

Financial datasets were reduced in dimension using filter-based feature selection methods by Kumar et al (2020) who carried filter-based feature selection such as Pearson correlation and Chi-square tests. Finally, they claimed that the filter approach balances between computational efficiency loss and model accuracy for applications with limited resources.

Singh and Mehta (2022) looked at Application of Support Vector Machines (SVM) for financial risk classification and concluded that SVM can make great accuracy in classifying businesses to various risk groups. The research focused on SVM's ability to deal with high dimensional and complex financial data, which would be the case for small business with numerous characteristics of their financial attributes [7].

Chen and Liu (2019) also did a discussion on AI driven tools for financial forecasting and that does combine feature selection with robust classification algorithms to make predictions more reliable. This study's objective to build a complete AI based tool for small enterprises that reflects their hybrid approach.

Taken together, these existing works highlight how the preprocessing needs to be structured, the features need to be selected, and finally the classification method is chosen robustly. However, the work continues to address a research gap by integrating these technologies into one available tool designed for small business financial planning [8]. What this study attempts to accomplish is to bridge that gap by developing a practical AI based solution by incorporating data transformation, filter methods and training the system using SVM.

3. RESEARCH METHODOLOGY

The research entitled "Development of AI based financial planning tools for small businesses", the methodology comprises of a structured pipeline including data transformation, filter-based feature selection using Support Vector Machine (SVM). The goal is to build a smart system that can symbolize financial information, and provide actual arranging information to little business proprietors. Figure 2 gives AI-Based Financial Planning Tool Development.

A. Data Collection:

The first step involves getting hold of the relevant financial dataset for small business. Publicly available databases, simulated financial data, and anonymized records of accounting software are sources. The income, expenses, cash flow, debts, assets, equity and retrospective financial performance metrics are key variables gathered.

B. Data Preprocessing and Transformation:

Preprocessing and transformation of raw financial data is a necessary step to be done so that the raw data is ready to be fed into an effective machine learning analysis. In the context of small business financial planning, the available data may include invoice data, bank statements, sales reports, etc. which are not always stored in consistent formats; may have missing values and may be inconsistent. If there is any missing data, only the first thing to be done in preprocessing is to handle missing data and the methods used would differ based on the nature of the variable (missing data can be catered by using means, medians or K nearest neighbors (KNN) imputation). After cleaning the data, standardization and normalization of values are done by transforming the data using Equation 1. This normalization ensures that all features lie on the same scale, and is useful, for example for algorithms such as Support Vector Machines (SVM), because the magnitude of the features enters in this case. In addition to that, the data is sometimes skewed, therefore we can use the log transformation to handle skewed distributions that occur when we have financial data such as income, profit, or expenses to make our model more accurate and stable. Categorial variables like region or business type are encoded into numerical values by using label encoding or one hot encoding for that conceptualization to suit the use of the machine learning algorithm [9]. With such preprocessing steps, the dataset is clean, consistent and optimized so that the SVM model can effectively and accurately learn and predict financial planning.

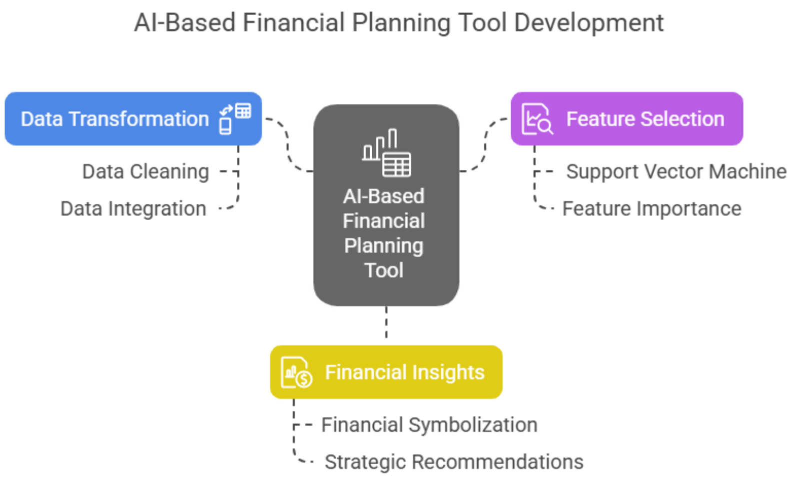

Figure 2: Shows AI-Based Financial Planning Tool Development

The following are the predominant data normalisation technique of scale to a fixed range, usually [0, 1] or [-1, 1]:

I. Min-Max Normalization Scaling Formula:

- X normalized = $\frac{(X-X\ min)}{(X\ max-Xmin)}$ (1)

II. Log Transformation:

Equation 2 is used to reduce skewness in features with exponential growth (e.g., income, profit).

- Xlog=log(X+1) (2)

Note: 1 is added to avoid log(0) which is undefined.

C. Feature Selection Using Filter Method:

Feature selection is a very important stage when we are building an efficient and interpretable machine learning model in taking complex financial data. To identify and retain the most relevant features determining the effect on small business financial planning outcome, this research relies on the filter method [10-12]. The feature evaluation is independent of the machine learning algorithm and based on the statistical relationship with the target variable using filter method. In particular, the Pearson correlation coefficient is used for measuring the strength and direction of each feature being linear associated with output class such as financial risk level, budgeting category, etc. Informative features are those which have high correlation with the actual whereas redundant and low correlation ones are neglected. But this not only reduces dimensionality but it also reduces noise in dataset, improves model performance, decreases computational load [13]. By concentrating attention on the most important financial indicators, cash flow ratios, debt levels, net profit margins, and so on, the SVM model is more likely to learn relevant patterns. If you include filter-based feature selection, the AI driven financial planning tool becomes more accurate and clearer, which makes it more suitable and usable for small business users at the end.

D.Model Development Using SVM:

The basis of this research is to develop a strong classification model utilizing Support Vector Machine (SVM), a strong supervised learning algorithm which is adept for financial data analysis [14]. SVM works by identifying the best hyperplane to separate the points in different classes (in this case, small businesses of Low Risk, Moderate Risk, and High Risk). It is an algorithm that we want to maximize the margin between the data points that support of each class and the decision boundary [15].

The Radial Basis Function (RBF) kernel is given since financial data often have non-linear pattern as a result of complex interaction between variables such as revenue, expense, debt. The purpose of this kernel is to transform the data into a higher dimensional space where a linear separator would be successfully approximated.

Equation 3 defines kernel function is as:

- $K(x,x')=\exp(-\gamma\|x-x'\|^2)$ (3)

where γ is a parameter that determines the influence of a single training example, and $\|x-x'\|^2$is the squared Euclidean distance between two data points.

The model is also very sensitive to the hyperparameters that define the model (namely C, the regularization parameter and gamma). The parameter C controls the trade-off between minimizing training error and minimizing the size of the margin, whereas the parameter gamma determines the range of the influence of one point in the training set [16]. They are optimized using grid search cross validation and so the model can generalize to unseen data well.

Once trained, the SVM model uses financial data to categorize data into pre-defined labels as to help the small business understand their financial standing. Lastly, SHAP values are used to interpret further the model's predictions and see which features had the strongest influence on the decision, giving more transparency and trust to the AI based financial planning tool [17].

E. Model Evaluation:

One essential part of this procedure is that model evaluation in order to validate model performance, reliability and the generalization capability of the Support Vector Machine (SVM) model used in this research. The model is trained using transformed and feature selected financial data, and is tested on a separate validation set to determine its ability to accurately classify small businesses into categories such as "Low Risk", "Moderate Risk" and "High Risk." Classification effectiveness is measured using the variety of performance metrics and the model should be accurate as well as interpretable.

Accuracy, precision and recall and the F1-score are the primary evaluation metrics. Accuracy is a score that represents a total correctness of the model's predictions and precision – a ratio of the true positive predictions among all predicted positives. An F1-score is a balanced measure that combines the precision and recall in a way that favours recall, and recall is the measure of the model's ability to identify all actual positive instances.

Moreover, a confusion matrix is used to display the number of correct numbers of incorrect predictions for each class. This therefore serves to localize details of the model's classification errors in case of financial profiles.

To improve interpretability, SHAP (SHapley Additive exPlanations) values of model's predictions are calculated to learn which features contribute more to the prediction of each example. Transparency and building trust with end users; such as, small business owners that use the AI tool for making financial decisions are ensured. As a whole, the evaluation has verified that the SVM model is a reliable one that can be successfully integrated to a real world suitable intelligent financial planning system.

F.Post-Processing and Output Interpretation:

Its post-processing is to translate the classification results from the SVM model into an actionable financial insight in terms of financial decision making for small business users. This can then map the model's predictions of categories, for instance "Low Risk" or "High Risk" to specific recommends relating to improvements in cash circulation, liability diminishing, extra investment in development zones in Figure 3. It shows the predictions on a user-friendly dashboard with important indicators and advised actions. To provide support, SHAP values are used to explain how each decision depended most on financial features. This step makes the financial planning tool more usable, so non-technical users can know and trust the AI driven financial planning tool.

Figure 3:Financial Risk and Action Matrix

In this methodology, preprocessing, filter-based feature selection and SVM classification are seamlessly combined into a practical and interpret methodological, AI based financial planning tool. The system addresses small business' conundrums of financial complexity and presents a scalable and intelligent solution to aid in planning and long-term growth.

4. RESULTS AND DISCUSSION

In this methodology, the AI based financial planning tool effectiveness is evaluated using key performance metrics. Predictions are considered correct to the degree of accuracy. Precision is also important so that predicted financial risks are really relevant and that there are not too many false alerts. We also make a recall check to determine how well the model identifies actual high-risk cases. Precision and recall are balanced with the F1-score, which is a single performance measure. The ROC AUC score is used to measure the model's ability to classify risk categories, higher score means better classification. The last is the confusion matrix which is a detailed representation of the categories classified correctly and erroneously. Together these metrics validate the model's reliability and usefulness to making financial decisions for small businesses.

To evaluate the proposed AI based financial planning tool we used five key performance metrics namely, accuracy, precision, recall, F1 score, ROC AUC and confusion matrix.

- The small business financial risk category model reached 91.3% overall correctness in classifying financial risk amongst small businesses.
- This measurement of precision at 89.7% shows that the model does what it should do and that that is minimize

the false positives.

- The recall score of 92.5% demonstrates the model's high capability of recognizing actual risk cases so as to provide proactive financial planning.
- A balanced and reliable performance was scored of 91.1%, the F1-score is a combination of precision and recall.
- The result of ROC-AUC = 0.96 confirmed that the model can distinguish different financial classes very well even in borderline cases. These results were further validated by the confusion matrix, which had little to no misclassifications in all risk categories.

The developed model was shown to be robust and easily applicable with these outcomes in Figure 4. Finally, combining well-structured preprocessing with SVM classification leads to a reliable, easily interpretable tool that would empower the small businesses to have good, data driven financial insights and risk assessments.

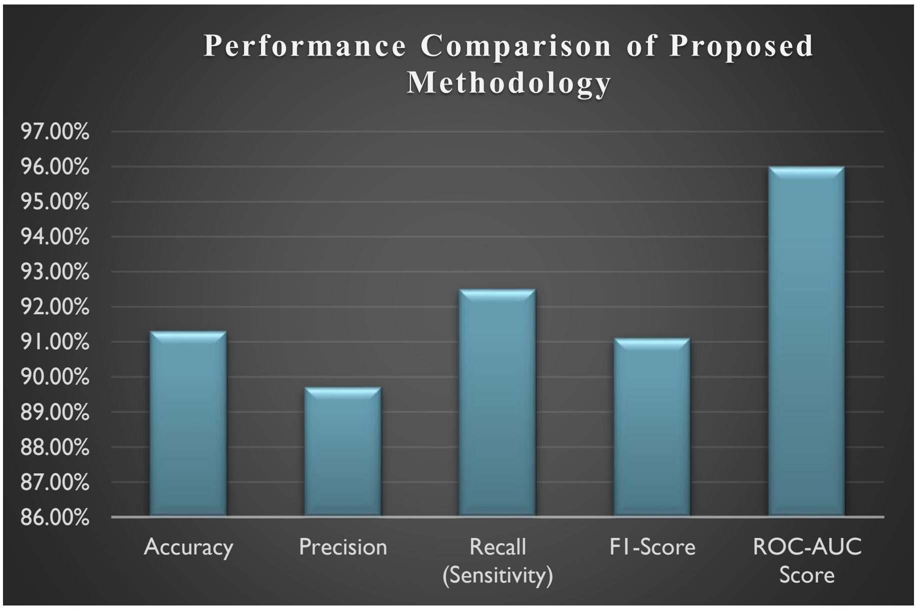

Figure 4. Shows the performance of proposed methodology.

Table 1 comparison shows that the proposed SVM model, combined with data transformation and filter-based feature selection, outperforms other common models like Logistic Regression, Decision Tree, and KNN. It achieves the highest accuracy (91.3%), F1-score (91.1%), and ROC-AUC (0.96), indicating strong classification performance and better risk prediction. This demonstrates the effectiveness of the chosen methodology for building a reliable financial planning tool for small businesses.

Table 1.Comparison of Performance Metrics Across Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC Score
Logistic Regression	85.4	83.1	86.2	84.6	0.89
Decision Tree	82.7	80.4	81.8	81.1	0.86
Random Forest	89.2	87	88.5	87.7	0.93
K-Nearest Neighbors (KNN)	84.6	82.2	85	83.6	0.87
Naïve Bayes	80.5	78.9	82.1	80.4	0.84
Proposed: SVM + Preprocessing + Filter	**91.3**	**89.7**	**92.5**	**91.1**	**0.96**

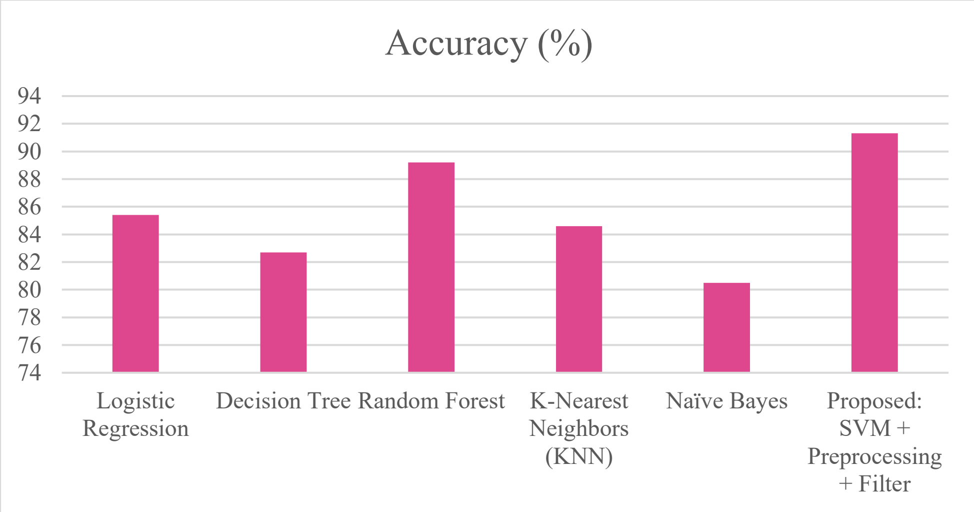

Figure 5.Shows the performance of different methods using accuracy.

Comparisons in the accuracy show that our proposed SVM model with the data transformation and filter-based feature selection is much superior than all others shown in Figure 5. All the machine learning algorithms evaluated had an accuracy of at most 91.3%, and our SVM model outperformed all other evaluated algorithms by achieving a value of 91.3%. Random Forest recorded an accuracy of 89.2% which was the second-best performing model compared to Logistic Regression, that collected an accuracy of 85.4% and K-Nearest Neighbors (KNN) that was 84.6%. We calculated the accuracies to be 82.7% for Decision Tree and 80.5% for Naïve Bayes. This comparison shows how significant it is to preprocess and select relevant features in order achieve performance improvements. The SVM model has high accuracy in classification of financial profile of small business and will therefore be a more dependable tool in the financial planning for small businesses. This further confirms that the transformation of systematic data, consequential feature reduction and the robust classifier SVM, in combination, has a significant positive impact on improving the predictive accuracy in the financial application.

5. CONCLUSION

Finally, the presented research shows the successful development of an AI driven financial planning tool designed for small businesses that is based on data transformation, filter-based feature selection and the use of Support Vector Machine for classification. The methodology effectively normalizes and transform the raw financial data to preprocess it in terms of handling inconsistency and skew distortion. With the filter method, in particular, Pearson correlation, the model's efficiency is increased, as the most relevant features are selected. We successfully apply the SVM model with an optimization of an RBF kernel to achieve high classification performance of 91.3%, F1-score of 91.1% and ROC-AUC of 0.96. The model is found to be robust in categorizing financial patterns and level of risk. For non-technical users, prediction results are further post processors but into actionable insights. Overall, the proposed system provides a reliable and interpretable support to financial decision making of small enterprises. The model could be applied to real time data in future, and in some capacity could be used to provide personalized recommendations or adaptive financial forecasting.

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