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ORIGINAL RESEARCH

Analysis of Taxpayer Behavior to Predict Motor Vehicle Tax Payments Using the Weighted Majority Voting Ensemble Approach

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Abstract

Taxpayer non-compliant behavior impacts Motor Vehicle Tax (MVT) revenues not following the predetermined targets. This behavior results in reduced income, and several regional development targets may not be achieved. Therefore, Regional Governments need to predict MVT payments to formulate future targets better. This research aims to analyze taxpayer behavior in predicting future MVT payments, whether the payments are compliant or late or non-payment. The proposed approach starts by analyzing and obtaining a dataset of taxpayer behavioral features. An ensemble classifier method based on Weighted Majority Voting (WMV) is used to predict payments. WMV was developed using the GridSearchCV technique to find optimal hyperparameter values to increase the model accuracy value for individual classifiers. The weight determined from the model accuracy value is converted into a ranking of the number of votes to maximize model performance. Next, feature ablation analysis is carried out to understand the contribution of each feature to model performance. The performance of the proposed system is evaluated using the confusion matrix, accuracy, precision, recall, and f1-score. The research results show that the WMV method performs better, with an accuracy of 96.247%, compared to the proposed individual classifier method in predicting MVT payments based on taxpayer behavior.

KEYWORDS:

Behavior Analysis, Feature Ablation Analysis, Motor Vehicle Tax, Payment Prediction, Weighted Majority Voting Ensemble.

1 | INTRODUCTION

Motor Vehicle Tax (MVT)[1] is a type of tax managed by local governments in Indonesia. MVT is one of the most significant tax contributors in financing regional development. Taxpayer compliance behavior in paying MVT is essential in achieving regional development targets. If taxpayers behave disobediently, they will tend to take tax avoidance actions that have the potential to reduce income and result in several regional development targets not being achieved. So, the Regional Government needs to make an effort to build a system that can analyze taxpayer behavior to predict future MVT payments. This system can help local governments make the right decisions to encourage or speed up late or non-payment MVT payments and better formulate future targets.

The challenge in this area is that taxpayer behavioral data is unavailable in raw data. Therefore, it is necessary to extract data to analyze and convert taxpayer data into a dataset with taxpayer behavioral features. This analysis uses data on motor vehicle taxpayer and their payment history over three tax years. Extraction of other information from taxpayers, from various actions local governments took to encourage or speed up taxpayers making payments.

Little research has been done into predicting tax payments. Most research tends to focus on taxpayer compliance, such as[2] [3] to determine the influence of the quality of MVT services on taxpayer compliance in paying MVT. Research[4] classifies the level of taxpayer compliance using data mining methods and a comparison of machine learning classification algorithms. Some other research focuses on predicting tax avoidance, such as detecting tax avoidance behavior based on publicly available financial data with a machine learning approach[5]. Research[6] detects tax evaders and predicts the amount of tax evaded using data mining methods.

Another machine learning method that can be used in prediction problems is the ensemble method. Although ensemble methods have been widely used in machine learning, they have not been widely applied to predicting MVT payments. Ensemble methods combine prediction results from several machine learning models to improve prediction accuracy and performance. Giving different weights to each model can prioritize better models in making final predictions. Hyperparameter optimization can influence the weight given to each model by increasing or decreasing the influence of each model in the voting process, which can ultimately improve the overall ensemble prediction accuracy[7].

This research aims to analyze the behavior of taxpayers to predict future MVT payments, whether they are compliant to pay (the motor vehicle is paid before the due date), late to pay (the motor vehicle is paid after the due date), or non-payment (the motor vehicle is not paid for even though it is past due). To produce more accurate predictions, in this research used an ensemble method that combines the K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Random Forest (RF) machine learning classification methods using Weighted Majority Voting (WMV). The ensemble method was developed by combining the WMV method and hyperparameter tuning Grid Search Cross-Validation (GridSearchCV) to find the best parameters for individual classifiers to improve the ensemble performance. The weight determined from the accuracy value of each model is converted into a ranking of the number of votes to enhance further the accuracy and precision of the overall ensemble predictions. Furthermore, in this research, an ablation feature analysis was also carried out to understand how each feature contributes to the prediction of MVT payments. The performance of the proposed system is evaluated using the confusion matrix accuracy, precision, recall, and f1-score, as well as by comparing the performance of each proposed method.

2 | RELATED WORK

A number of studies have explored analyzing payment behavior by utilizing various available information and predicting payments using machine learning algorithms. This indicates a high level of interest in understanding how people behave when it comes to payments, especially in business and financial contexts. Researchers[8] predict the electricity payment behavior classes of residential customers, to improve customer service and reduce the late or non-payment of electricity bills. This research analyzes customer payment behavior using historical information on customer electricity bill payments. Then, group customer classes using the k-means algorithm and use five data mining algorithms to predict customer models. The research results show that the Random Forest algorithm is the right choice to predict customer class and is the right strategy to increase customer satisfaction and increase revenue.

Researchers[9] predict the online purchasing behavior of customers. Every customer activity is stored in a database to collect information such as how customers spend their valuable time and days to decide to buy goods or not. The most frequently purchased items and the number of purchases are also taken into consideration. Datasets are used to analyze and categorize customers based on their purchasing behavior. Inventory and sales data sets available on the internet were also used in this research, and their performance was evaluated using algorithms. Classification is carried out with the Support Vector Machine (SVM) algorithm, and the SVM model is built with a linear kernel. The research results show that the proposed methodology can better analyze customer purchasing behavior.

Researchers[10] analyzed and predicted customer churn behavior using Bayesian classification algorithms, Random Forest, and Support Vector Machine to attract new customers and retain old customers. Prediction data is collected via web log files and used for analysis. Log files are collected for at least two years to calculate customer churn more accurately. A year consists of festival days, regular days, and restricted days. A detailed analysis of the prediction results via the voting method is carried out to measure the performance of the collective approach. The performance of the proposed system is evaluated through accuracy, precision, recall, and f-score analysis. The research results show that the level of accuracy of the collective data collection method is better than other homogeneous methods.

Researchers[11] proposed a model to detect electricity theft behavior from electric vehicle charging poles based on the Support Vector Machine (SVM) algorithm. Extracting features from historical data and real-time data of electric vehicle charging poles from electric vehicle users such as electric feature information, electric magnitude, voltage, current, user information features, and power factor (daily power consumption, monthly maximum demand), which are used to classifying electricity theft behavior. The results show that this SVM algorithm's accuracy and recall rates are better than the Logistic Regression and K-Nearest Neighbor (KNN) algorithms.

Researchers[12] aim to detect customers with fraudulent behavior in water consumption. This fraudulent behavior results in non-technical losses and loss revenue. This research uses two classification algorithms, SVM and KNN, to detect customers who commit fraud. This model was built using historical meter consumption data from customer water bills and extracts profiles of customers who commit fraud. The data covers five years of customer water consumption with historical records of 1.5 million customers for 90 thousand customers. 1294 customer profile datasets were used for training and testing SVM and KNN, with 10-fold cross-validation and holdout methods. Experiments show that SVM and KNN achieve good performance with an overall accuracy of about 70

Researchers[13] predict tax default using machine learning algorithms. Data about taxpayers, such as income, deductions, and credits, as well as tax laws, such as tax rates and other information, are collected for predictive purposes. Algorithms such as C4.5, Random Forest, Gradient Boosting, Artificial Neural Networks, and Support Vector Machine have proven helpful in predicting tax default. Meanwhile, to further improve the performance of machine learning techniques, ensemble methods such as Stacking and Bagging can be used. The results of this research show that machine learning techniques can be used to predict tax default with high accuracy.

Researchers[14] predicted dengue fever (DHF). Data was collected from January 2020 to June 2021. The dataset consists of 315 instances, 18 attributes, and one target. In the proposed model, Random Forest is used to diagnose the class or level of dengue fever using a hyperparameter tuning approach with GridsearchCV for prediction. The 10-fold cross-validation technique was applied to overcome the model bias problem. Experimental analysis shows that the accuracy for Random Forest with GridsearchCV is 100% for the training dataset and 98.79% for the testing dataset. Meanwhile, comparative analysis shows that the ensemble model in multilabel DBD classification provides better precision, recall, and f1-score than other machine learning models.

3 | MATERIAL AND METHOD

The proposed system workflow consists of several stages, as shown in Figure 1 . The steps start with data analysis to obtain a dataset with taxpayer behavioral features. Next, data preprocessing and feature selection are carried out to build the model. The model is built using an ensemble method that combines WMV with hyperparameters and optimized weights. Ablation feature analysis is applied to understand the contribution of each feature in the prediction. The final stage is the confusion matrix, which measures the model's prediction performance and describes how often the model predicts correct and incorrect classes.

3.1 | Data Collection and Processing

TABLE 1 Taxpayer Data

No	Description
1	The name of the taxpayer
2	Taxpayer address
3	District code
4	Village code
5	Resident association number
6	Neighbor association number
7	Police number
8	Vehicle class
9	Vehicle sub-class code
10	Vehicle country code of origin
11	Vehicle brand code
12	Vehicle type code
13	Year of the vehicle
14	Payment date
15	Due date
16	Nominal MVT payment

The data analysis stage is divided into two parts, namely, data collection and processing. At the data collection stage, raw data was collected as motor vehicle taxpayer data at the East Surabaya Samsat Joint Office, East Java province, Indonesia. The data consists of taxpayer subject data, motor vehicle object data, due date, payment date, and nominal MVT payment, which can be seen in Table 1 .

At the data processing stage, data analysis is carried out to obtain a dataset with taxpayer behavioral features by extracting taxpayer data and other information from taxpayers. Local governments have taken various actions, namely that MVT payments can be made in cash and non-cash via EDC machines or E-Samsat (bank e-channel, e-wallet, marketplace, minimarket, and PPOB). If the taxpayer exceeds the due date and has not made payment, the taxpayer will receive a reminder message, which also functions as a bill for tax arrears/receivables for late MVT payments through the issuance of tax letters. Another action is to issue a policy by holding a bleaching program, where this program eliminates/exempts fines for late payment of MVT to lighten the burden on taxpayers in fulfilling the obligation to pay MVT every year.

Extractions carried out on taxpayer data include:

1. Name and address data are used for data extraction. The new feature is created based on the total number of vehicles owned by the taxpayer and the total nominal MVT amount owned by the taxpayer.

2. Name, address, payment date, and due date data are used for data extraction. The new feature is created based on the number of vehicles and nominal MVT compliant, late, and non-payment.

3. Data on due dates and payment dates per nopol in January for the 2019, 2020, and 2021 tax years are used for data extraction. The new feature is created based on the difference in days between the due date and the payment date, whether the payment is compliant, late, or non-payment. The feature is filled with 0 if compliant, 1 if late, and 2 if non-payment.

4. The new feature is created based on the number of days difference between the due date and payment date for three tax years (2019, 2020, 2021) per nopol, which can be exemplified as follows:

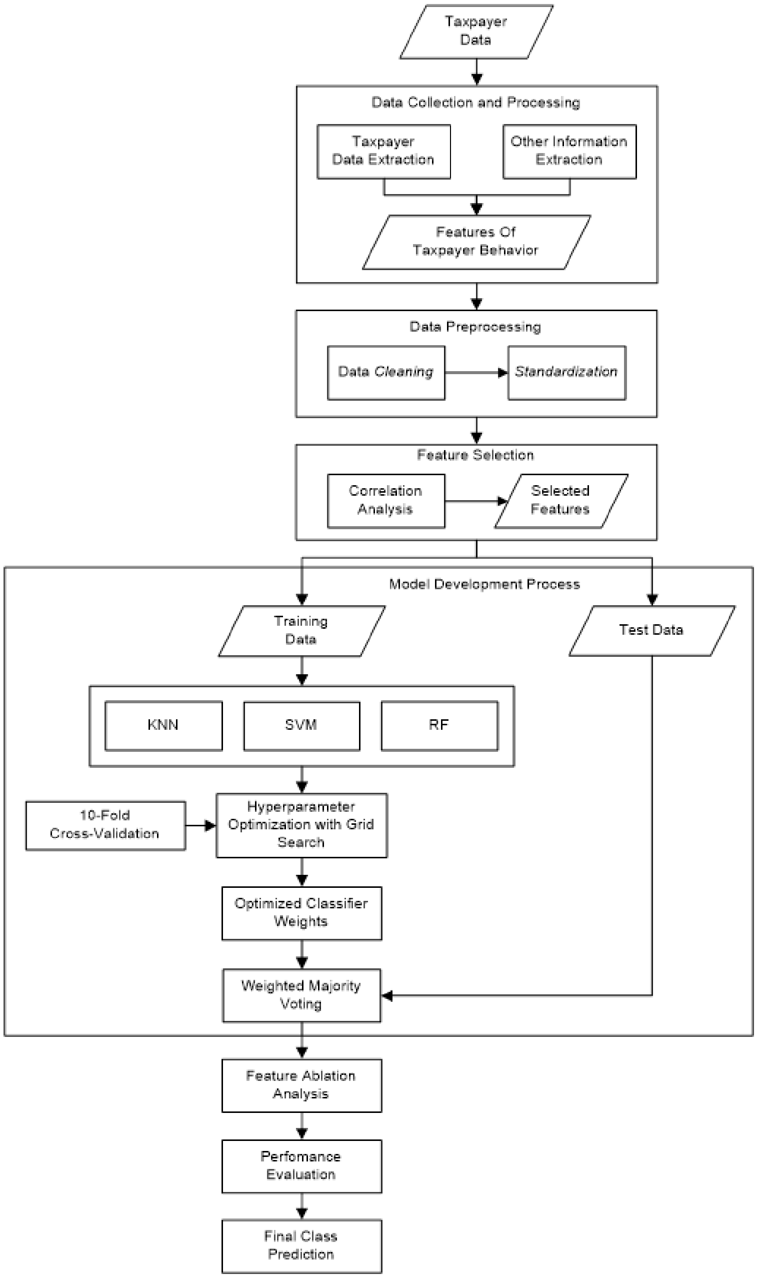

FIGURE 1 Workflow of the proposed system

(a) nopol L 1 A in January of the 2019 tax year, payment is made 2 days earlier than the due date (compliant), so that the difference in days is -2;

(b) nopol L 1 A in January of the 2020 tax year, payment is made 5 days after the due date (late) so that the difference in days is equal to 5;

(c) nopol L 1 A in January of the 2021 tax year, payment is made 10 days after the due date (late) so that the difference in days is equal to 10;

(d) the sum of the difference in days from points a – c above is -2 + 5 +10 = 13;

(e) if the sum result is negative, which means compliant, the feature is filled with 0. If the sum result is positive and not more than 365 days, which means late, then the feature is filled with the number 1, but if the sum result is positive and more than 365 days, which means non-payment, then the feature is filled in with the number 2.

5. Data on the due date and payment date for the 2021 tax year is used for the new feature to find out the latest condition of the taxpayer. Whether the taxpayer only made 1 payment or more than 1 payment or did not make any payment in the 2021 tax year. The feature is filled with 0 if make 1 payment, 1 if more than 1 payment, and 2 if don't make any payment.

6. The new feature is created based on the number of days difference between the due date and payment date from the payment history for the 2021 tax year in taxpayer data. An example of a taxpayer with the initial R in the 2021 tax year makes 2 payments, which can be explained as follows:

    (a) Nopol L 2 A in January of the 2021 tax year, payment is made 3 days after the due date (late), so the difference in days is equal to 3;

    (b) Nopol L 3 A in March 2021 tax year, payment is made 5 days earlier than the due date (compliant), so that the difference in days is -5;

    (c) The sum of the difference in days from points a and b above is 3 + (-5) = -2;

    (d) If the sum result is negative, which means compliant, the feature is filled with 0. If the sum result is positive and is not more than 365 days, which means it is late, then the feature is filled with the number 1, but if the sum result is positive and is more than 365 days, that means it is non-payment, then the feature is filled with the number 2.

Extraction of other information from taxpayers, from various actions taken by local governments to speed up payments, including:

1. The new feature was created based on information on payment methods for three tax years (2019, 2020, 2021) per nopol, whether payment is made via cash, EDC, or E-Samsat. The feature is filled in by adding the number 1 if it is via cash/EDC/E-Samsat and the number 0 if it is not via cash/EDC/E-Samsat.

2. The new feature is created based on information on tax letters for three tax years (2019, 2020, 2021) per nopol, which makes payments beyond the due date plus 15 days to 29 days, where the local government will collect by issuing a letter SPOS taxation (tax object and subject data collection letter). The feature is filled in by adding the number 1 if it is late beyond the due date plus 15 days to 29 days and filled in by adding 0 if not.

3. The new feature is created based on information on tax letters for three tax years (2019, 2020, 2021) per nopol, which makes payments beyond the due date plus 30 days to 59 days, where the local government will collect by issuing a letter NPP taxation (tax calculation note). The feature is filled in by adding the number 1 if it is late beyond the due date plus 30 days to 59 days and filled in by adding 0 if not.

4. The new feature is created based on information on tax letters for three tax years (2019, 2020, 2021) per nopol, which make payments more than 59 days from the due date, where the local government will collect by issuing a letter NTP taxation (Tax Bill Note). The feature is filled in by adding the number 1 if it is more than 59 days late from the due date and filled in by adding 0 if not.

5. The new feature was created based on information on the bleaching program for three tax years (2019, 2020, 2021) per nopol, whether payments were made during the bleaching program, where there was a write-off/exemption of MVT fines, even if payments were late. The feature is filled in by adding the number 1 if the payment is made within the bleaching schedule and by adding 0 if the payment is made outside the bleaching schedule.

3.2 | Data Preprocessing

The data preprocessing stage is the initial stage of data mining to change and process data into a dataset in a format that is suitable for the system and ready for analysis[15]. In the initial stage, a data cleaning process is carried out[16] to check whether there is data with null values. To improve the performance of the method, standardization is needed[17] to scale each input variable by subtracting the mean and dividing it by the standard deviation so that the distribution has a mean of 0 and a standard deviation of 1.

3.3 | Feature Selection

This feature selection function is to reduce and determine important features in making predictions so that there will be an increase in accuracy with a lighter computational load. In this research, feature selection is implemented using the correlation analysis method[18]. Correlation is a feature selection method for analyzing the strength of the relationship between two or more variables. The level of stability of the relationship is expressed in numbers, which can be seen in Table 2 . The stronger the correlation value between two variables, the more identical the variables are[19]. In this study, features that have a correlation coefficient value of more than 0.8 can be selected by selecting one of the two features that have a very strong relationship. In contrast, other features with a correlation coefficient value below 0.8 are chosen for use in the next process.

TABLE 2 Correlation Coefficient Value

Value Intervals	Relationship Level
0.000 – 0.199	Very Weak
0.200 – 0.399	Weak
0.400 – 0.599	Moderate
0.600 – 0.799	Strong
0.800 – 1.000	Very Strong

3.4 | Classification Methods

In the model-building process, machine learning classification methods are used in predictions. Hyperparameter Tuning with GridSearchCV is applied to find optimal parameters for each machine learning model used.

3.4.1 | K-Nearest Neighbor

K-Nearest Neighbor (KNN)[20] is a classification method that works by comparing training data and testing data. Look for data patterns that are closest to the test data. KNN assumes that something similar will exist nearby or next door. KNN uses all available data and ranks new data or cases based on similarity measures or distance functions. Distance calculations, such as Cosine, Manhattan, and Euclidian distances, can be used to find the closest similarities. The level of accuracy with the KNN method is greatly influenced by the number of nearest neighbors, namely the optimal k-value. The k value in the KNN method determines the number of neighbors that will be tested to determine the classification of a particular query point.

3.4.2 | Support Vector Machine

Support Vector Machine (SVM)[21] is a classification method to find the best hyperplane for separating classes. To reduce classification errors on each training dataset sample, the Cost (C) parameter is used. The higher the C value, the smaller the classification error. Conversely, the lower the C value, the higher the error rate that occurs. SVM uses kernel functions to map input space to feature space. Some kernel functions are linear and RBF (Radial Basis Function). The choice of kernel type used will affect the resulting accuracy value. Another parameter of SVM is Gamma. Gamma determines how much influence a single sample (point) of the training dataset has. High gamma means that the points must be very close to each other to be included in the same class. Low gamma means a wide similarity radius, which results in more points being grouped in the same class.

3.4.3 | Random Forest

Random Forest (RF)[22] is a machine learning method in the form of ensemble learning, which combines several decision trees to produce more accurate predictions. RF consists of many trees obtained through a bagging or bootstrap aggregation process.

Several N decision trees are combined to create an RF. Each tree in the RF provides a class prediction. The category prediction with the most votes becomes the model prediction candidate. Several parameters in RF, namely the criterion used to measure split quality, the criteria supported are gini and entropy for information acquisition. The max _eatures parameter is the maximum number of features the model needs to consider when searching for the best split. The n_estimators parameter determines the number of trees in the forest to be used in the model.

3.4.4 | Weighted Majority Voting

Weighted Majority Voting[23] is a method that trains a number of different single classifiers. Each single classifier produces output in the form of a class label. Next, the class label output produced from each single classifier is combined, and the final class label is determined, which is taken from the majority of class labels based on the weight given to each single classifier. For certain classes where the classification performs better, the weight is higher. The use of this method is expected to improve the performance of the classification model because each classifier has different advantages, and this method combines these advantages to produce better accuracy.

3.4.5 | Optimizing Hyperparameter Tuning with the GridSearchCV

Hyperparameter tuning is an important step in optimizing machine learning model performance, and one effective approach is to use Grid Search with 10-fold cross-validation. Grid Search is used to test each combination of hyperparameters that have been determined so that the best parameter combination can be found that can improve model performance. Additionally, 10-fold cross-validation was used to measure model performance more accurately and avoid overfitting. By dividing the data into 10 subsets, the model is trained and tested 10 times, resulting in a more stable estimate of the extent to which the model can be applied to never-before-seen data. Overall, the combination of hyperparameter tuning with GridSearchCV aims to find the optimal parameter combination, which can help improve model performance in making more accurate predictions[24].

3.5 | Feature Ablation Analysis

Ablation feature analysis is used to show the effectiveness of the method and the influence of each feature on the method's performance[25]. This process is done by deleting features individually until all features have been selected and the classification process is carried out[26]. The main goal of feature ablation analysis is to understand and measure the extent to which each feature plays a role and contributes to optimizing the model and improving prediction results.

3.6 | Performance Evaluation

The model performance was evaluated using the confusion matrix and classification report[27]. Confusion matrix is a table used in evaluating the performance of a classification model, which displays and compares the actual values with the values predicted by the model. The results of the classification process in the confusion matrix are true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN). This research uses three class labels, so the dimensions of the confusion matrix are 3×3.

From the results of the confusion matrix, accuracy, precision, recall, and f1-score can be calculated to produce a classification report. Accuracy gives an idea of the extent to which the model is correct in making predictions, which is determined by dividing the ratio of correct predictions by the total number of predictions (1). Precision helps measure the extent to which the positive predictions made by the model are correct and the degree of accuracy of the positive predictions (2). Recall helps measure the extent to which the model is able to identify all true positive instances (3). F1-score evaluates the extent to which a classification model can achieve a balance between precision and recall (4)[5].

Formulas to calculate performance metrics:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$precision = \frac{TP}{TP + FP} \tag{2}$$

$$recall = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1-score} = \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \times 2 \tag{4}$$

4 | RESULT AND DISCUSSION

This section presents and discusses the results obtained by completing the workflow of the proposed system. Experiments and simulations were conducted using Jupyter Notebook software, Python programming language version 3.8.5, and Scikit-learn version 0.24.2.

4.1 | Dataset Results

Analysis carried out in the data collection and processing process resulted in a dataset with taxpayer behavioral features, as seen in Table 3 . The resulting dataset has 21 features and one class labelling feature. The class contains three labels, compliant, late, and non-payment, which are targets for model predictions. The data generated was 1,865, consisting of 1,076 compliant data, 640 late payment data, and 149 non-payment data.

FIGURE 2 CF KNN

FIGURE 3 CF SVM

FIGURE 4 CF RF

FIGURE 5 CF WNV

TABLE 3 Behavior-Based Taxpayer Dataset Features

No	Feature	Description
1	JKEND	The total number of taxpayer vehicles
2	JPKBKEND	The total MVT nominal amount of the taxpayer
3	JKENDTAAT	The number of taxpayer vehicles that are compliant with the tax
4	JPKBKENDTAAT	The nominal amount of MVT taxpayers who are compliant with pay
5	JKENDTELAT	The number of taxpayer vehicles that are late paying
6	JPKBKENDTELAT	The nominal amount of MVT taxpayers who are late paying
7	JKENDTDKBYR	The number of taxpayer vehicles that non-payment
8	JPKBKENDTDKBYR	The nominal amount of MVT taxpayers who are non-payment
9	TH2019	Taxpayer data per nopol for the 2019 tax year: 0: Compliant, 1: Late; 2: Non-payment
10	TH2020	Taxpayer data per nopol for the 2020 tax year: 0: Compliant, 1: Late; 2: Non-payment
11	TH2021	Taxpayer data per nopol for the 2021 tax year: 0: Compliant, 1: Late; 2: Non-payment
12	MSLAKU	The number of differences between payment date and due date per nopol for tax years 2019, 2020, and 2021: 0: Compliant, 1: Late; 2: Non-payment
13	BYR2021	The number of taxpayer data for the 2021 tax year:0 : 1 payment, 1: more than 1 payment; 2: do not make payment
14	MSLAKU2021	The number of differences between payment date and due date per taxpayer for the 2021 tax year:0 : Compliant, 1: Late; 2: Non-payment
15	TUNAI	Taxpayer data per nopol in cash: 0: Non-Cash, 1: Cash
16	EDC	Taxpayer data per nopol via EDC: 0: Not EDC, 1: EDC
17	ESAMSAT	Taxpayer data per nopol via E-Samsat: 0: Not E-Samsat, 1: E-Samsat
18	PUTIH	Taxpayer data per nopol made during the bleaching schedule: 0: Not Bleaching, 1: Bleaching
19	SPOS	Taxpayer data per nopol that exceeds the due date plus 15 days up to 29 days: 0: Not SPOS, 1: SPOS
20	NPP	Taxpayer data per nopol that exceeds the due date plus 30 days up to 59 days: 0: Not NPP, 1: NPP
21	NTP	Taxpayer data per nopol that is more than 59 days from the due date: 0: Not NTP, 1: NTP
22	STATUS	Class labels: 0: Compliant, 1: Late, 2: Non-payment

5 | CONCLUSION

In this research, extraction and analysis of the MVT payment behavior of taxpayers have been carried out to obtain a dataset that will be applied in predictions. The Weighted Majority Voting Ensemble method, developed by optimizing GridSearchCV hyperparameter tuning and optimizing the weights for individual classifiers (KNN, SVM, and RF), is proposed to predict three classes of MVT payment behavior (compliant, late, non-payment) more accurately. Ablation feature analysis is applied to understand the contribution of each feature in predicting class. The performance of the default model is evaluated and compared with the model performance of the proposed method. Experimental results show that the accuracy for default KNN, SVM, RF, and WMV is 90.080%, 94.102%, 94.906%, and 94.638%, respectively. Meanwhile, the accuracy for KNN, SVM, RF, and WMV with the proposed method is 90.349%, 95.442%, 95.710%, and 96.247%, respectively. Ablation feature analysis is effective in identifying features that are less relevant or redundant, as well as those that have a positive impact or show high relevance in predicting MVT payments. Therefore, overall, the method proposed in this research can increase the accuracy of predicting taxpayer behavior classes in making MVT payments and is an appropriate strategy to help achieve regional development targets.

In future research, the dataset can be developed by adding features based on the behavior of other taxpayers and using different machine learning methods to increase the diversity of comparisons of MVT payment prediction results. You can also use different feature selection and optimization techniques in making model predictions.

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CREDIT

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