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Optimization of Multi-Layer Perceptron in Ensemble Using Random Search for Bankruptcy Prediction

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Abstract: A corporation is in financial trouble if it has money problems but has yet to be bankrupt. Companies' financial woes must be identified early to implement various bankruptcy avoidance strategies. This study discusses the optimization of the multi-layer perceptron ensemble stacking classifier hyperparameter by majority voting as a methodology for constructing a classification model for bankruptcy prediction (MLP-STM). The primary aim of this study is to create a reliable model for use in MLP-STM-based financial ratio analysis. The used MLP-STM model has successfully optimized the MLP hyperparameters, which is a substantial contribution and a novel aspect of our study. Training and evaluation data came from a multi-class dataset with labels such as "distress area," "grey area," "safe area," and "save area." The training dataset is pre-processed to be well accepted by the learning ensemble. All performance models are evaluated using their confusion metrics and the Area Under the Curve (AUC). The primary conclusion of this study is that a novel MLP-STM classification model with varying hyperparameters can effectively classify features for detecting the performance of financially troubled businesses. When compared to the MLP-BAM and MLP-BOM models, the MLP-STM model performed best, with a 97% accuracy rate and a 100% AUC value. The results of this research have important implications for the banking and finance industries, including developing an early warning system in the event of financial bankruptcy.

Keywords: MLP-STM, Optimization Hyperparameter, Prediction

Introduction

Deep learning, ensemble learning, cloud computing, machine learning, and artificial intelligence development are some of the latest emerging technologies in the software sector. They are also frequently used in the financial industry (Syed Nor *et al*., 2019). While other technologies are available and more widely used, Machine Learning (ML) is currently more popular for data analysis. Chen *et al*. (2020) demonstrated that ML allows for faster, more accurate, and cheaper data analysis as it produces faster results and helps in drawing multiple conclusions (Pisula, 2020) Fig. 1: Application of ensemble learning. The ensemble learning approach is used across a variety of industries, including fraud detection, sentiment analysis, healthcare, video analytics, e-commerce, and banking.

Every business has the danger of running into financial difficulties. When a business experiences financial difficulties, its operations are hampered due to money problems (Jan *et al*., 2018). Financial problems and unpaid debts are common indicators of a failing business. (Mehreen *et al*., 2020) say that cutting or stopping dividend payments is another sign of financial problems.

We devise a plan for processing the data set and focus on making our analyses and predictions more accurate. Science aims to methodically learn more about the world around us based on physical facts, which is what we mean when we talk about prediction. Prediction issues can be tackled with the help of machine learning algorithms. Classification techniques are the most important part of ML (Horak *et al*., 2020; Hartini *et al*., 2021).

This means studying data to develop rules that can classify or recognize new data that has never been looked at before.

Our aim is to create a reliable classification model to help businesses, identify financial ratio, including crisis, uncertainty, and stability. In addition, we first made literary observations related to our earlier work (Altman, 2013; Abdullah, 2021; Pisula, 2020; Siswoyo *et al*., 2022; Safi *et al*., 2022)

The banking ratio finance dataset is what we use to train and test the hyperparameters of our multilayer perceptron when it is used to predict bankruptcy.

The following are the original contributions of this study: (1) A robust ensemble learning based strategy for analyzing bank failure categorizations; (2) Using the random search method for hyperparameter optimization. (3) Finding a new ensemble stacking model with various basic algorithm variants.

One of the most active fields in recent times, bankruptcy prediction analysis utilizing ensemble learning, has seen an increase in research activity year after year (Barboza *et al*., 2017; Faris *et al*., 2020; Siswoyo *et al*., 2022)

The overarching purpose of this research is to develop a reliable system for predicting bankruptcies. For a good reason, many researchers have concentrated on the problem of bankruptcy prediction. One helpful tool for this is the Altman Z-score, which employs financial ratios to categorize financial distress. Abdullah (2021), have put the bankruptcy prediction model through its paces using several statistical methods like discriminant analysis, logistic regression, an artificial neural network, SVM, bagging, boosting, and random forest. An accuracy of 87% was found (Barboza *et al*., 2017; Shrivastava *et al*., 2020).

Overall, the machine learning model outperformed the traditional one by 10%. Concerning accuracy, the bagging, boosting, and random forest models fare the best, while the RF algorithm scores 87%, LR scores 69%, and discriminant analysis score 50%. Shrivastava *et al*. (2018); Rustam and Saragih (2018).

Overall model accuracy of 151 studies analyzed by Marso and El Merouani (2020). The ANN model has an rage accuracy of almost 84%, the SVM model is almost 83%, and the DT model is almost 80%. When comparing the frequency of type I and II errors, ANN has a lower rate than SVM. The Case Based Reasoning (CBR) model that works alone turns out to be the least accurate of all the Artificial Intelligence (AI) tools.

Predicting bankruptcy using a convolutional neural network is an idea put forward by Cialone (2020). As part of his analysis, he compares CNN models with others, such as Logistic Regression (LA), Classification Tree (CART), Support Vector Machine (SVM), and Boosted Neural Network (BPNN) models. About 96% of the predictions made by the model are correct.

For bankruptcy forecasting, (Iturriaga and Sanz, 2015; Gogas *et al*., 2018; Horak *et al*., 2020) also compared the SVM kernel with RBF and BPNN. After researching the available options, they settled on a BPNN structure with one hidden layer containing nine neurons and a pair of output neurons. They found that BPNN is superior to SVM. The precision rate is 95%.

Based on the work (Siswoyo *et al*., 2020), to classify bank failures using the ensemble bagging approach, and hyperparameter optimization. Several factors affect the effectiveness of the bagging ensemble, which are related to the quantity, quality, or characteristics of the data. The choice of the right algorithm and parameter settings greatly affects the level of accuracy. The ensemble bagging model has shown 96% success in experiments.

After comparing the results of studies in machine learning and AI. Can see the limitations of each study and how the strategy is recommended. Table 2 the comparative findings of other undergraduate studies. In this article, we have implemented a bankruptcy classification prediction model. As a result of this study, we have discovered a new use of the bankruptcy prediction model. To do this, we use a random search method based on an ensemble majority vote.

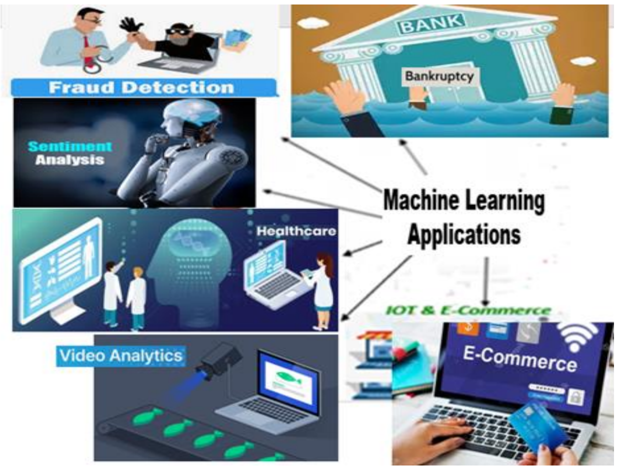

Fig. 1: Application of ensemble learning

Materials and Methods

Propose Framework

Multiple approaches are becoming increasingly popular for forecasting and categorizing insolvency. This research uses a categorization model to foretell the type of bank bankruptcy. Figure 2 depicts the big picture of the suggested categorization model. More information is gathered and studied through pre-processing, identifying training and test data, ensemble learning classification, optimization of MLP hyperparameters, experimental results, and model comparison.

Data Collection and Exploration

The information used in this study comes from the financial statements of eleven banks that were made public on the website https://www.ojk.go.id or the individual banks' websites between 2010 and 2016. Target areas are categorized as either "distress areas," "grey areas," or "save areas." When there are fewer banks in the "distress area" and "grey area" than in the "Save Area," the data becomes uneven. To correct this, the Synthetic Minority Oversampling (SMOTE) algorithm is used (Faris *et al*., 2020).

This research relied on data from the following, https://repository.uinjkt.ac.id/dspace/bitstream/123456789/40734/1/ZULFIKAR%20HADAD-FEB.pdf. Four financial metrics serve as inputs in this data collection:

1. Working capital to total assets
2. Earnings before interest and taxes to total assets
3. Return earnings to total assets
4. Book of the value of equity to book value to total debt and one data in the form of output: Z-score

Dataset Preprocessing

The goal of performing data preparation before deploying the model is to boost its efficiency (Rusdah and Murfi, 2020). This emphasizes the significance of finding outliers in the data. The discrepancy results from an inequity between the percentage of enterprises in the financial distress area, a grey area, and a safe area. We use the over-sampling technique to rectify the data imbalance.

We also looked for any blanks, but there were not any. We have to transform the labels in the target column of the data set of numbers because they will cause issues. The scikit-learn library's label encoder class is used here. The desired variable has been encoded into a numeric value by the label encoder.

Financial distress, a financial grey area, and a financial savings area are the variables to be measured. When developing a model, the most crucial feature is that it has already been established that the class imbalance problem impacts the inaccuracy of the classification problem. Specifically, we employ oversampling in this study. Figure 3 displays the oversampling results. An indicator of oversampling and sampling (Shrivastava *et al*., 2020).

K-Fold Cross Validation

K-fold cross validation may be performed by dividing the data into training and testing sets. To put the model to the test, we will separate the data into training and testing sets (to train the model). To do this, we will set $K = 10$, where the data will be ten times longer than the data in the first fold and serves as a test set while the remaining folds are used for training (Tembusai *et al*., 2021).

MLP Architecture

Optimizing hyperparameters for Multi-Layer Perceptrons is the focus of this study (MLP). Input, hidden, and output layers comprise the feed-forward Artificial Neural Network (ANN) known as Multi-Layer Perceptron (MLP). A DNN is an MLP with several hidden layers (Abdullah, 2021).

The network's structure is determined by factors like the number of layers it has, the number of hidden-layer neurons it employs, and the goal function it is trained.

This research proposes a random search strategy for locating the optimal neural network in MLP concerning the metrics above: Accuracy, precision, recall, and *F*1-*score*. We then experimented with several distinct designs and hyper-parameter settings, as detailed below:

- We consider two possible outcomes in the case of NL with multiple hidden layers. After each iteration, the random search algorithm generates an output by randomly altering the number of layers. The optimal number of layers is determined by a grid search method
- Two cases are considered for the number of neurons in each hidden layer (nr). A random search algorithm unpredictably shuffles the number of neurons. The number of neurons to use is determined by the grid search algorithm
- Activation function, Random Search; the activation function (Relu, Tanh, or Sigmoid) is tested in each trial. Grid Search specifies the number of activation functions, such as Relu, Tanh, and Sigmoid, from which algorithms can pick
- Hyperparameter optimization using Adam, Sg, Adaleta, Adamax, Nadam, and lbfgs with an MLP optimizer

Hyperparameter Modification

Random search is employed as a method for optimizing hyperparameters. The random search tuning strategy investigates a limited region of the algorithm's hyperparameter space, assessing the performance of each resulting configuration (Li and Talwalkar, 2020).

The random search algorithm pseudo code is shown in Fig. 4 random search algorithm.

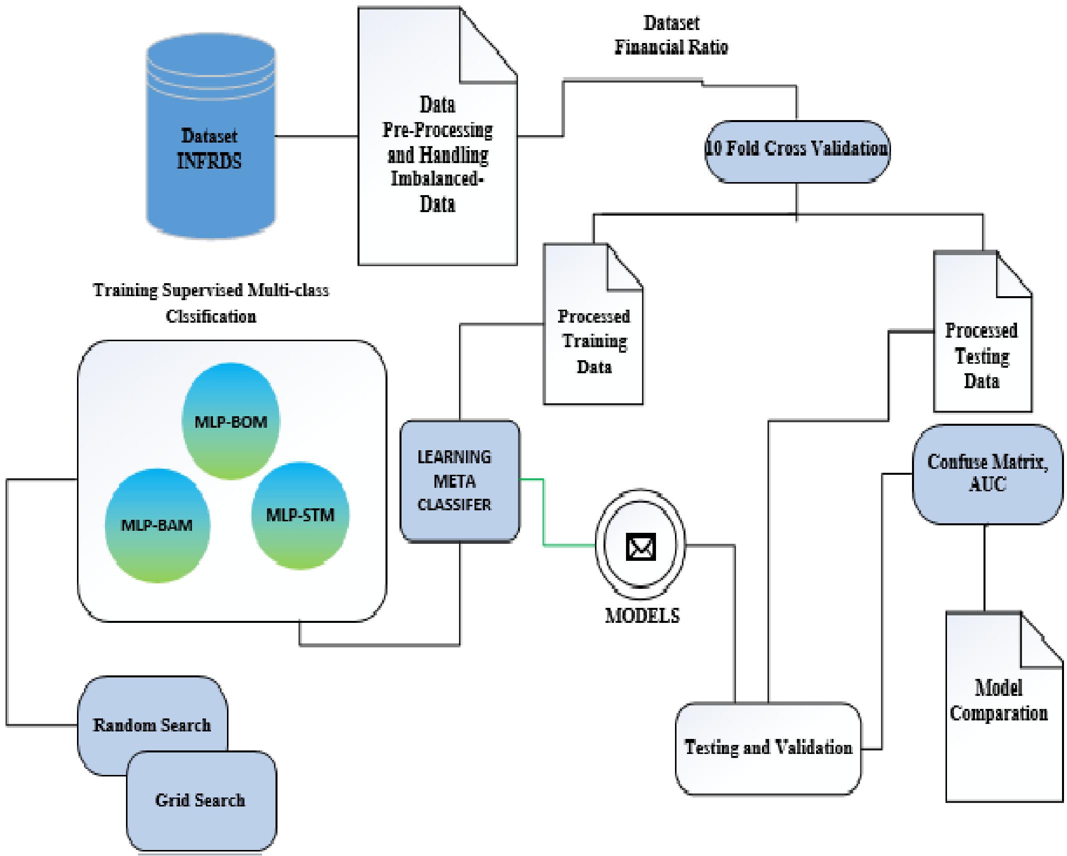

Fig. 2: Bankruptcy classification model framework

The results of hyperparameter optimization of the random search algorithm are shown in Fig. 5 distribution of random search values.

Activation Identity, Solver LBFGS

The activation of nonlinear identity, represented by the parameter values shown in Fig. 5, was found using the random search algorithm. In cases where this identity affects how well the network model learns from the training dataset, the procedure for optimization limited-memory this approach is invariant to gradient scaling and is computationally efficient when applied to the Broyden-Fletcher-Goldfarb-Shannon (L-BFGS) algorithm. Optimal for use cases with extremely noisy data or hazy gradients. The best value for the learning rate is 0. Increasing the learning rate causes the data convergence speed to increase but at the cost of less stability. While three hidden layers with 10, 20, and 5 neurons are preferable, such numbers are not optimum. Where the hidden layer aids convergence, 100 is the maximum epoch allowed.

Random Search Algorithm

We apply the random search algorithm to the financial ratio dataset to obtain the optimal MLP hyperparameters. According to Li and Talwalkar (2020), the random search approach will select a value from a probability distribution to determine the optimal setting for each hyperparameter. If it is possible to have better hyperparameter values and high feature dimensions, then the random search will have lower computational costs (Li and Talwalkar, 2020). The MLP model will undergo hyperparameter optimization in this investigation Fig. 5 displays the results.

Model Experiment

When the classification model is applied to the training data, it will produce a model. A model can be categorized as a good model if the model can explain the data without being affected by noise. A good model will have high accuracy, and the AUC value is also significant.

Evaluation and Validation

The confusion matrix method will evaluate the model. The confusion matrix provides information that compares the estimation or prediction results from the model with the actual results, which are the truth values.

Confusion Matrix

The confusion matrix is a tool to measure the performance of the classification model, where the output is

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a table with four model variables that differ from the predicted and actual values.

The four model variables that represent the results of the classification process are (i) *TP* is the label of the data that is predicted to be true is true (true positive). (ii) *FP* is a data label predicted to be real but false (False Positive). (iii) The *TN* variable is the label of the data that is predicted to be false and true-false (True Negative). Finally, (iv) *FN* is the label of the data that should be predicted to be false but true (false positive).

The values of the model variables used are:

Accuracy

Accuracy is an evaluation to measure the number of predictions the model obtains correctly. The formula for accuracy is given below:

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

Formula 1 is used to calculate the accuracy of a model. Whereas precision evaluates how accurately the model predicts positive labels. Precision is the percentage of relevant results. The precision formula can be written as follows:

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

Formula 2 is used to calculate the relevant precision or presentation. Recall calculates the percentage of actual positives that were correctly identified (true positive). The recall formula can be written as follows:

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

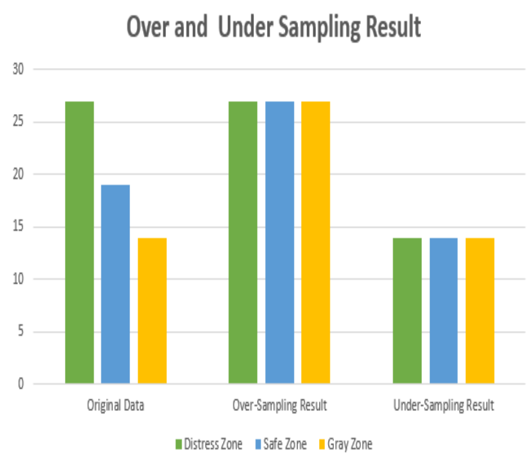

Fig. 3: Oversampling and under sampling graph

Step 1:	**Initialize** the population with randomly generated solutions
Step 2:	**repeat**
Step 3:	Create a new solution using **Differential Evolution algorithm**
Step 4:	**If the new solution is better than the worst solution in the population then**
Step 5:	**Replace** the worst solution by the new solution **End if**
Step 6:	**until** the maximum number of iteration as been
Step 7:	reached
Step 8:	**Return** the best solution

Fig. 4: Random search pseudo code

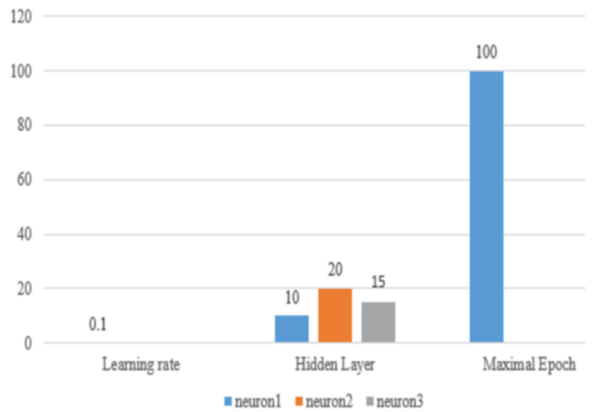

Fig. 5: Distribution of random search values

Formula 3 is used to calculate recall or the actual percentage of positives that are correctly identified. The *F*1-*score* maintains a balance between precision and recall for the classifier performed.

If the precision is low, the *F*1-*score* will also be low, and if the recall is low, then the *F*1-*score* is also low; the *F*1-*score* in the multi class dataset is calculated as follows:

$$F1-score = \frac{2\times(Recall\times Precision)}{Recall+Precision} \tag{4}$$

Formula 4 is used to calculate the *F*1-*score* of a model. The *F*1-*score* value is a balancing value between precision and recall (Muchori, 2017; Abdullah, 2021). Therefore, the *F*1-*score* is an assessment that performs better if the model is only assessed with precision or recall.

The AUC score is a sensitivity descriptor that implies the overall effectiveness of the model. The AUC curve is based on the value obtained in the calculation with the confusion matrix, which is between the False Positive Rate (FPR) and True Positive Rate (TPR).
where:

$$FPR = \frac{FP}{FP+TN} \tag{5}$$

In this study, the process stages were carried out following a predetermined procedure to obtain a strong and stable model. The dataset collected is used as four predictor variables, namely Working Capital to Total Assets (WCTA), Retained Earnings to Total Assets (RETA), that has been obtained. The framework model for the Proposed Classification of Financial Distress is generally the class division of this category refers to the Altman Z-Score method (Altman *et al*., 2017) based on the dataset Book Value of Debt (BVEBVTD). And the target of two variables, namely Z-Score and class. Where is the class category: (i) Save Zone, (ii) Gray Zone, and (iii) Distress Zone? (RETA), Earnings Before Interest and Taxes to Total Assets (EBITA), and a book value of equity to total.

Experiments

Experiment Setup

Experiments were carried out on a quality bank financial ratio dataset. Some basic algorithms such as Random Forest (RF), Logistic Regression (LR), Support vector machine, and Artificial Neural Network (ANN) are used as reinforcement in the new classification model of MLP hyperparameter optimization based on ensemble bagging, ensemble boosting, and ensemble stacking, where the new model.

This will improve the performance of the financial distress classification model. In this study, we apply random and grid search methods to optimize the MLP hyperparameters. The results of the two algorithms in the form of the best parameters are shown in Tables 1 and 2.

The research was conducted by conducting six scenarios as follows:

- Research 1 (Exp 1): Applying the results of the hyper-parameter optimization of the grid search method to the bagging ensemble
- Research 2 (Exp 2): Applying the results of hyperparameter optimization of the random search method to the bagging ensemble
- Research 3 (Exp 3): Applying hyperparameter optimization of grid search method ensemble boosting
- Research 4 (Exp 4): Applies the results of hyperparameter optimization of the random search method to ensemble boosting
- Research 5 (Exp 5): Applying the results of the hyperparameter optimization of the grid search method to ensemble stacking
- Research 6 (Exp 6): Applying the results of hyperparameter optimization of the random search method on ensemble stacking

The experiment was conducted using a computing platform based on an Intel Core i3 2.2 GHz CPU, 12 GB RAM, and a 64-bit Microsoft Windows 10 Professional operating system. The development environment is Jupyter, the Python programming language. The default parameter settings provided by the Python 3.6 library are used to apply the MLP random search method hyperparameter optimization to ensemble learning.

The experimental process of the proposed model will be validated using the Confusion Matrix (CM) and Area Under Curve (AUC) methods. If the AUC is close to a value of 1, then the classification model can be stated as a classification model that has good performance. The dataset used for validation is a new dataset, which is not included in the training data. Each data set will be K fold cross validation to be separated into a training set and a test set. The model is hoped to provide a stable, unchanged output value.

The unbalanced dataset will be used as a balanced dataset using the oversampling method. Initialization of algorithm parameters used for classification is essential to get the best performance from the classification model. At the same time, the initialization values for the classification model parameters in the experiment are shown in Table 1.

The application of the Grid search algorithm model using python coding is shown in Fig. 6. MLP Hyperparameter Grid Search. While the implementation of the Random search model using python coding is shown in Fig. 6 random Search hyperparameter MLP.

Data Validation

The application of fold cross-validation in sharing training and test data has been proven to achieve the target classification model with a more stable and robust performance. Where the fold method will divide the data as much as 'k' fold, where k = 5 or k = 10, where fold one is used as test data while the rest becomes training data, will be done as much as 'k', test data and training data will be automatically sequential.

Evaluation

Evaluation of the results is the last stage in the research, drawing the results and discussion into conclusions and suggestions. The conclusion will answer the research objectives and answer the problems discussed. Suggestions will be given for further research by looking at the results of this study and how to improve the results in the future.

```
MLP-OP=MLPClassifier(Solver='lbfgs', activation=
'Identity', alpha=0.1, hidden_layer_sizes=(10,20,5),
rando_state=1, max_iter=1500, verbose=10, learning
rate_init=0.1
```

Fig. 6: Random search hyperparameter MLP

Table 1: Detail of parameter setting in classifier

Classifier	Parameter value
LR	MutliClass = 'multinomial', Random_state = '1'
SVM	C = 1.0, kernel = 'linier', degree = '3', gamma = 'auto', probability = 'true'
Random forest	n_estimator = '10', class_weight = 'balanced', random_state = '1'
Optimization random search MLP	Activation ='identity', learning_rate = '0.1', input layer= '5' hidden layer = '3' outpot layer = '1' Training cycle ='1500', Leraning rate = 'constant', solver ='lbfgs', random_state ='1', verbose = '10'
Optimization grid search MLP	Activation ='tanh', alpha = '0.0001', input layer = '1' hidden layer ='3' outpot layer = '1' Training cycle ='1000' Leraning rate = 'contant', solver = 'adam'

Table 2: Comparison results of researchers' other

Author	Methods	Accuracy%	Object	Finding	Unlimited
Shrivastava *et al*. (2018)	Bagging, boosting, stacking, RF, SMOTE, and Lasso, regression,	87.30	Failure prediction of Indian	ML models can be utilized for creating model with better classification Correctness (Alaka *et al*. (2018)	Does not apply k-fold cross validation and parameter optimization ANN, SVM, DT
	84.00		Analyzing a whole the different model	NN performance is higher compared to other methods	The pre-processing stage is not comprehensive
Faris *et al*. (2020)	NN convolutional, ANN, DT, LR, SVM,	96.00	ANN performance is higher compare, MDA, AdaBoost,	ANN performance is higher compared to other methods	Encoding image menjadi features tidak sempurna
Horak *et al*. (2020)	SVM, RBFN, BPNN	97.00	The implication of machine learning for financial solvency prediction	Ensemble classifier outperforms all other models'	Not applying parameter optimization
Abdullah (2021)	Altman Z-Score, machine learning, ANN, ensemble	88.00	Financial solvency Prediction	The ensemble outperforms of all other models	Applied default parameters
Safi *et al*. (2022)	Metaheuristic optimization, neural network, ensemble learning	96.00	Optimization-Based Neural Network with Ensemble Learning for Financial Distress	PSO and CSO can optimize ANN, used in homogeneous ensemble learning systems	PSO fast find local Solution
Siswoyo *et al*. (2022)	Altman Z-score, ensemble stacking, optimization MLP	97.00	Bankruptcy classification using optimization hyperparameter-based MLP and ensemble learning	MLP, which is utilized inhomogeneous ensemble learning, can be improved by random search	Not yet applied to the manufacturing and retail industries

Note(s): Artificial Neural Networks (ANN), Bayesian Networks (BN), Classification and Regression Trees (CART), Data Envelopment Analysis (DEA), Decision Trees (DT), Financial Ratios (FR), K-Nearest Neighbor (KNN), Logistic Regression (LR), Multilayer Perceptron (MLP), Multivariate Discriminant Analysis (MDA), Radial Basis Function Network (RBFN), Random Forest (RF), Stacked Models (SM), Support Vector Machines (SVM), Particle Swarm Optimization (PSO)

Results

The experiment results by applying a new hyperparameter optimization classification model based on ensemble bagging, ensemble boosting, and ensemble stacking. The best accuracy rate is 97% by ensemble stacking. While Fig. 6 applies the random search and random search hyperparameter optimization methods on MLP using python coding.

In the random search method, the solver parameter values, activation, alpha, hidden layer, iteration, and learning rates have been determined after testing the dataset and algorithm of each algorithm.

Figure 6, the parameters used are shown; the hidden layer is given three pairs with the number of neurons 15, 10, and 5. Solver = 'lbfgs', activation = 'Identity', alpha = 0.1, hidden-layer-sizes = (10,20,5), random-state = 1, max-iteration = 1500, verbose = 10, learning rate-init = 0.1

The experimental results based on the six classification models on the financial ratio dataset and the parameters obtained are shown in Table 2 comparison results of researchers other.

Six new ensemble classification models that apply the random search and grid search methods to the optimization of the MLP algorithm have been carried out in experiments 5 and 6. The ensemble stacking classification model has the best accuracy value, with an accuracy rate of 97%. For comparison, the bagging ensemble classification model has an accuracy rate of 96%, and the ensemble has an accuracy rate of 95%.

Discussion

To build a better bank bankruptcy prediction model. We implement the MLP-STM model. The results of previous bankruptcy prediction studies had an accuracy value of 92% (Marso and El Merouani, 2020) and 83.33% (Fallahpour *et al*., 2017). Meanwhile (Safi *et al*., 2022) conducting research on the application of PSO and CSO hyperparameter optimization based on neural network ensembles, the results are almost the same as research on the MLP-STM model (97 vs. 98%). However, the layers are hidden (four layers compared to six layers). This results in a model with a smaller size and faster time inference. It is suitable to run on devices with limited resources.

The results of the comparison of studies with the same dataset using different ensemble models are shown in Table 2, indicating that the effectiveness of the proposed solution can also be found in similar work, such as using hyperparameter random search optimization and grid search.

Table 2 that the effectiveness of the proposed solution can also be found in other work, such as using PSO and CSO hyperparameter optimization based on majority vote ensembles (Safi *et al*., 2022) or applying optimization of machine learning algorithms to predict bank bankruptcy (Siswoyo *et al*., 2022).

Conclusion

We have processed banking financial reports to build a financial ratio dataset using the Altman Z-Score model with the outputs: 'Distress area', 'Grey area', and 'Save is'. The majority of voice learning ensembles by applying the hyperparameter have processed banking financial reports to build a financial ratio dataset using the Altman Z-Score model with the outputs: 'Distress area', 'Grey area', and 'Save is'. The majority of voice learning ensembles have been proposed and applied by applying the hyperparameter random search optimization method and the grid search method in this study. Research results can help the finance department predict if bankruptcy is possible. We have applied many classifiers and performed training comparisons in accuracy and AUC values for data and the data tester random search optimization method and the grid search method have been proposed and applied in this study. Research results can help the finance department and also predict if there is a possibility of bankruptcy. We have applied many classifiers and performed training comparisons in accuracy and AUC values for data and data tests.

This study can be helpful in many industries if implemented successfully and is also different from existing technology. The paper has described the algorithm and the classification model using ensemble learning, which is also the current market trend. The MLP-STM model is a promising addition to existing models when dealing with classification and bankruptcy prediction problems, with an accuracy rate of 97% and an AUC value of 100% in the test data set, which outperformed studies on the same data set. In the future, we will expand the dataset to add more financial ratio datasets for retail and manufacturing companies. In addition, MLP hyperparameter optimization with random and grid search methods will be applied to other classification algorithms.

The effectiveness of the proposed solution can also be found in similar work, such as using GBM-based ensembles in the comparative evaluation and bankruptcy analysis for businesses (Pisula, 2020) or applying optimization of machine learning algorithms to predict bank bankruptcy (Siswoyo *et al*., 2022).

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Author’s Contributions

Bambang Siswoyo: Design research plans and organize research; participated in all experiments, coordinated data collection, data analysis, data interpretation, and critically reviewed articles for intellectually significant content, implemented. The proposed method and perform all trials, and provide the final approval of the items to be submitted and any revised versions.

Zuraida Abal Abas: Participate in all experiments, coordinate data acquisition, data analysis, and data interpretation and critically review articles for intellectually significant content and provide the final approval of those to be submitted and any revised versions.

Ahmad Naim Che Pee: Participate in coordinated data acquisition, coordinated data analysis, contributed to the written of scripts, and provided final approval of any to be submitted and revised versions.

Rita Komalasarii, Heri Purwanto, Eri Satria and Dadang Sudrajat: Participated in coordinated data collection, coordinated data analysis and data interpretation, and contributed to written the manuscript.

Ethics

This article is unique and contains unopened material. The authors of the comparisons state that all the different authors have read and supported the composition; moreover, no moral issues are included.

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