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An Enhanced Ant Colony Optimisation Algorithm with the Hellinger Distance for Shariah-Compliant Securities Companies Bankruptcy Prediction

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ABSTRACT

This study addresses the challenge of applying ant colony optimisation algorithms to imbalanced datasets, focusing on a bankruptcy dataset. The application of ant colony optimization (ACO) algorithms has been limited by their performance on imbalanced datasets, particularly within bankruptcy prediction where the some of bankruptcy cases leads to skewed data distributions. Traditional ACO algorithms, including the original Ant-Miner, often fail to accurately classify minority classes, which is a critical shortcoming in the context of financial distress analysis. Hence, this study proposes an improved algorithm, the Hellinger Distance Ant-Miner (HD-AntMiner), which employs Hellinger distance as the heuristic for ants to gauge the similarity or dissimilarity between probability distributions. The effectiveness of HD-AntMiner is benchmarked against established classifiers—PART and J48—as well as the conventional Ant-Miner, using public datasets and a specialized dataset of 759 Shariah-compliant securities companies in Malaysia. Utilising the Friedman test and F-score for validation, HD-AntMiner demonstrates superior performance in handling imbalanced datasets compared to other algorithms, as affirmed by the Friedman test. The F-score analysis highlights HD-AntMiner's excellence, achieving the highest F-score for Breast-cancer and Credit-g datasets. When applied to the Shariah-compliant dataset, HD-AntMiner is compared with Ant-Miner and validated through a t-test and F-score. The t-test results confirm HD-AntMiner's higher accuracy than Ant-Miner, while the F-score indicates superior performance across multiple years in the Shariah-compliant dataset. Although the number of rules and conditions is not statistically significant, HD-AntMiner emerges as a robust algorithm for enhancing classification accuracy in imbalanced datasets, particularly in the context of Shariah-compliant securities prediction.

Keywords: Ant colony optimisation, bankruptcy prediction, Hellinger distance, Shariah-compliant securities.

INTRODUCTION

Bankruptcy prediction is essential for all businesses to monitor respective financial statements in avoiding corporate bankruptcy. Through a bankruptcy prediction model, enterprises would be alerted to notice bankruptcy signs by determining whether the signs correspond to the financial statement. Firm managers could act swiftly with appropriate actions to resolve relevant issues by assessing the details of financial statements with the bankruptcy prediction results. Besides reducing the time required to determine risky financial statements, an efficient model also provides high prediction accuracy to prevent corporations from massive losses. While traditional methods employ mathematical functions to predict bankruptcy (Uthayakumar et al., 2020a), the latest machine learning (ML) algorithms are the popular method to predict bankruptcy. Although the number of successful companies is larger than that of bankrupted firms, imprecise bankruptcy prediction remains the main challenge, primarily due to the imbalanced dataset.

Ant colony optimisation (ACO) is a popular algorithm for conducting approximate optimisation (Dorigo et al., 1996) by serving as the first swarm intelligence-based metaheuristic algorithm to imitate the ant foraging behaviour in a colony. The algorithm has solved many real-world issues, including the travelling salesman problem (Dorigo & Gambardella, 1997), scheduling (Wang, 2021; Sharma, 2022; Elcock & Edward, 2023), and industrial challenges (Dzalbs & Kalganova, 2020). Dorigo and Blum (2005) employed the ACO algorithm to resolve a tedious combinatorial challenge in the 1990s. Subsequently, Parpinelli et al. (2002) introduced the Ant-Miner algorithm based on ACO to extract classification rules from data. Ant-Miner is a robust algorithm compared to other famous taxonomy algorithms. Past experimental results discovered the acceptable performance of Ant-Miner with simpler laws. Nonetheless, Ant-Miner is only competent for a balanced dataset and unsuitable for an imbalanced version.

Despite the versatility of the ACO algorithm like Ant-Miner in addressing classification problems, a significant gap persists in its application to bankruptcy prediction due to the prevalence of imbalanced datasets. These datasets, wherein the instances of bankruptcy are substantially outnumbered by non-bankruptcy instances, present a skewed distribution that traditional ACO algorithms struggle to interpret accurately. This imbalance results in a classification bias towards the majority class, leading to a high rate of misclassification of the minority class, which, in the context of bankruptcy prediction, is often the class of interest. The Ant-Miner, while robust for balanced datasets, exhibits limitations when applied to imbalanced datasets. Hence, there is a need for an enhanced ACO-based algorithm that can effectively navigate through the complexities of imbalanced data, particularly for predicting the bankruptcy of Shariah-compliant securities companies where the cost of misprediction is especially high. Therefore, this study incorporates the Hellinger distance to improve discrimination power and prediction accuracy. By addressing this need, the study aims to contribute a more precise tool for financial risk assessment and aid in the early detection of bankruptcy, particularly within the unique context of Shariah-compliant financial entities where conventional prediction models may not suffice.

Veganzones and Séverin (2018) explained that a bankruptcy prediction model is inaccurate when most datasets contain a class monopoly rate exceeding at least 80 percent. Therefore, the Hellinger Distance Ant-Miner (HD-AntMiner) algorithm was proposed with the Hellinger distance as the heuristic of ants, as the Hellinger distance is skew-insensitive and functions optimally with imbalanced datasets (Cieslak & Chawla, 2008). The study hypothesised that the HD-AntMiner algorithm could resolve the discrimination power of the majority classes and increase the accuracy of bankruptcy prediction compared to the ACO-based Ant-Miner. We compared the proposed algorithm to three algorithms: Ant-Miner, PART (Frank & Witten, 1998), and J48 (an implementation of the C4.5 algorithm in Weka) (Quinlan, 1993), which is the industry-standard algorithm for data classification to predict the bankruptcy of Shariah-compliant securities companies in Malaysia. Specifically, the bankruptcy of Shariah-compliant securities enterprises would depend on the Malaysian legal system. The companies adhere to the Shariah law, which is different from conventional companies that do not adhere to any religious law (Hayat et al., 2014).

RELATED WORK

Imbalanced Datasets

Classes exhibit an unequal distribution, creating imbalanced datasets (He & Garcia, 2009). One can measure the severity of imbalance through the imbalanced ratio (IR). For example, only 10 percent of the individuals in a dataset are diagnosed with the disease, while the remaining are healthy. As such, the dataset achieved a 10 percent IR, whereas the majority class dominated 90 percent of class labels in the dataset. In the bankruptcy dataset, the number of successful companies was generally higher than that of bankrupt companies. Zalenkov and Volodarskiy (2021) proposed and examined a multi-objective classifier selection (MOCS) algorithm on a dataset of

2457 Russian companies, with 456 declared bankrupt and a dataset of 5910 Polish companies with 410 declared bankrupt. The MOCS algorithm could improve the prediction results by considering the classification as a multi-objective optimisation challenge, minimising the parameters of false positive rates (FPRs) and false negative rates (FNR), and developing a prediction algorithm as an ensemble.

Borowska and Stepaniuk (2022) postulated a rough-granular approach (RGA) model to resolve the imbalanced dataset issue and enhance classification efficiency. The RGA model was proven effective regarding the Area under the ROC curve (AUC) and recall measures on a severely imbalanced dataset. Meanwhile, Mushava and Murray (2022) developed an alternative technique, namely the quantile function of the generalised extreme value (GEV) distribution, as a link function in extreme gradient boosting (XGBoost) to improve the categorisation of an imbalanced dataset. To address the multiclass imbalanced problem, Sainin et al. (2021) experimented with the design of the meta-classifier ensemble, which is a combination of sampling and feature selection. The findings demonstrated that the design through sampling and feature selection with the ensemble classifier method via the random forest and AdaboostM1 led to a significant improvement. Huang et al. (2022) also discovered that the primary indicator of balanced data is the equivalence of the gradient norms of positive and negative classes. The neural network algorithm for highly imbalanced data classification (NN_HIDC) propounded a controllable gradient rotation strategy to determine local boundary expansion for positive samples.

Cieslak and Chawla (2008) introduced the Hellinger distance as a decision tree splitting criterion in another work dealing with an imbalanced dataset. Cieslak et al. (2012) extended the previous work by proposing an alternative decision tree technique through the Hellinger distance as the splitting criterion, namely Hellinger distance decision trees (HDDTs). The results revealed the high practicality of HDDTs with bagging without any sampling method for an imbalanced dataset. In a pioneer study, Razali et al. (2021) developed an improved algorithm, Hellinger-ant-tree-miner (HATM), inspired by the ACO meta-heuristic. The HATM algorithm outperformed the existing algorithm, namely ant-tree-miner (ATM), regarding minority class prediction (MCP) and F-measure. Razali et al. (2022) extended the work by splitting the datasets into 70 percent training and 30 percent testing domains compared to the initial study with 90 percent training and 10 percent testing domains. The study experimented with real-world data, revealing that the HATM algorithm outperformed the original ATM algorithm, a result validated by the Friedman test.

Ant Colony Optimization

Numerous research works in recent years have utilised ACO to resolve classification and optimisation challenges. Uthayakumar et al. (2020a) developed an ACO-based financial crisis prediction (FCP) algorithm through a combination of ACO-based feature selection (ACO-FS) and ACO-based data classification (ACO-DC) algorithms. The ACO-FS algorithm underwent a comparison with three other FS algorithms, namely the genetic algorithm (GA), particle swarm optimisation (PSO) algorithm, and grey wolf optimisation (GWO) algorithm. Meanwhile, they compared the ACO-DC method with other state-of-the-art methods regarding classification outcomes. The ACO-FCP method was a superior algorithm, which outperformed other compared methods. Subsequently, Uthayakumar et al. (2020b) expanded the scope by employing an ACO-based Ant-Miner algorithm to perform bankruptcy prediction and credit risk analysis qualitatively and quantitatively. The study concurrently developed an effective swarm intelligence-based classification rule induction (CRI) framework. The proposed approach demonstrated more accurate results in multiple performance analysis factors compared to other classifiers, such as the radial basis function (RBF), random forest (RF), logistic regression (LR), and multilayer perceptron (MLP).

Hashemi et al. (2022) introduced an alternative technique, wherein the ACO algorithm is based on the collection of heuristics through the multi-criteria decision-making (MCDM) method by propounding that multiple heuristics would perform more optimally than a single heuristic. Specifically, the movement of the ants follows multiple criteria instead of a single criterion. Meanwhile, an alternative ACO variant, namely focused ACO (FACO), was introduced by Skinderowicz (2022) to limit the number of differences between a newly constructed and a selected prior solution. The findings discovered that FACO outperformed ACO when resolving large travelling salesperson problem (TSP) instances with reduced required time. Furthermore, a hybrid of ML and ACO (ML-ACO) was proposed to enhance meta-heuristics to resolve combinatorial optimisation challenges (Sun et al., 2022). They tested the ML-ACO algorithm on various classification algorithms, including support vector machines, logistic regression, and graph neural networks. The results demonstrated that the proposed algorithm consistently improved ACO performance.

METHODOLOGY

This study improved the work of Parpinelli et al. (2002) by implementing the Hellinger distance as the heuristic of ants. The following section outlines the method of the proposed algorithm in this study.

Hellinger Distance-AntMiner (HD-AntMiner)

The if-then rule expresses the discovered classification knowledge as follows:

IF < conditions > THEN < class >

The *IF* component comprises a set of conditions generally connected by a logical operator (*AND*). The *THEN* component specifies the class predicted for cases with predictor attributes satisfying all terms in the *IF* component. Each term presents a <attribute, operator, value> triplet, as illustrated in the following example of the rule structure:

IF Sector = Construction AND Gross Margin = (0.045, ∞),
THEN Status = Bankrupt.

Sector and *Gross Margin* are the attributes employed to classify whether the corporations went bankrupt. The algorithm classifies the class as bankrupt when all conditions are fulfilled.

1) Construction representation

The construction graph of the HD-AntMiner algorithm is identical to the ACO algorithm, with all nodes fully connected throughout the path (see Figure 1). Figure 1 depicts the selected path with solid lines and the potential path to be employed by ants with dashed lines. The rule structure is expressed as follows:

IF Attribute 1 = $v_{1,2}$ AND Attribute 2 = $v_{2,3}$ AND Attribute n = $v_{n,2}$
THEN Class = Class 1.

Figure 1

Rule Construction Representation of HD-AntMiner

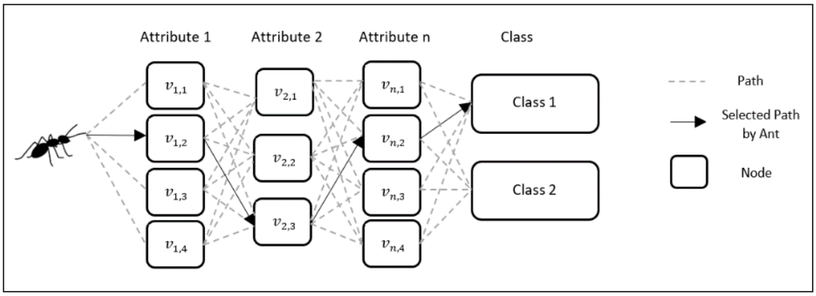
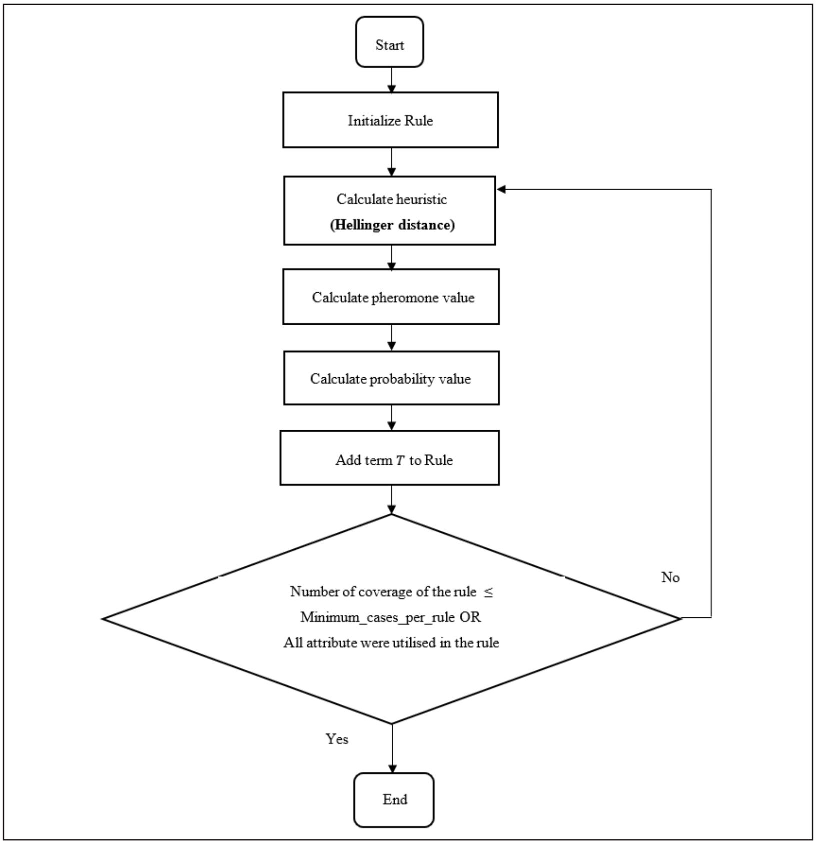


Figure 2

The Process of Generating One Rule



2) Rule generation

The algorithm employed the sequential covering approach to discover the list of classification rules. Initially, the number of discovered rules was zero in the training set. Each iteration will discover one rule for inclusion in the classification rule list and remove the related rows from the training set. The process of generating one rule is illustrated in Figure 2. The rule generation process terminates upon fulfilling one of the stopping criteria:

i. A rule encompassing several cases under a pre-defined number identified as *minimum_cases_per_rule*.
ii. The ant utilised all attributes.

3) Heuristic function

The HD-AntMiner algorithm computed the value HD_{ij} of a heuristic function for each $term_{ij}$ and add it to the current rule. The heuristic function estimates the quality of the term, which concerns the ability to improve the prediction accuracy of the rule. The Hellinger distance employed in the HD-AntMiner algorithm is an enhancement of the Hellinger distance by Cieslak et al. (2012) and serves as the heuristic of ants. Equation 1 expressed the Hellinger distance. In $P(Y = y \mid X = x)$, y is derived from a certain finite set of classes, such as $+$ and $-$, and x is derived from a finite set of attribute values, including $\{sunny, overcast, rain\}$

$$HD\big(P(Y_+), P(Y_-)\big) = \frac{1}{\sqrt{2}}\left(\sqrt{P(Y_+ \mid X_i)} - \sqrt{P(Y_- \mid X_i)}\right)^2 \quad (1)$$

where,

$HD\big(P(Y_+), P(Y_-)\big)$ is confined in $\left[0, \sqrt{2}\right]$,

$HD(\cdot\,,\cdot)$ is symmetric and positive,

$HD\big(P(Y_+), P(Y_-)\big) = HD\big(P(Y_-), P(Y_+)\big) \geq 0$,

The squared Hellinger distance is the lower bound of the Kullback-Leibler divergence (Nguyen et al., 2007).

4) Rule pruning

Rule pruning removes unnecessary terms to improve predictive capability and simplicity, as a more concise rule is less complicated to comprehend. Q is the value of rule quality, where $0 \leq Q \leq 1$ is expressed in Equation 2:

$$Q = \frac{TP}{(TP\ + FN)} * \frac{TN}{(FP\ + TN)} \tag{2}$$

where,

TP = true positive,
TN = true negative,
FP = false positive,
FN = false negative.

5) Pheromone update

The pheromone update of the HD-AntMiner algorithm indicates the evaporation of ant pheromones in the real world. All terms began with the same quantity of pheromones. All paths also contained the same quantity of pheromones when the first ant commenced the search, as expressed in Equation 3:

$$\tau_{ij}(t = 0) = \frac{1}{\sum_{i=1}^{a} b_i} \tag{3}$$

where, a_i = the number of attributes,

b_i = the potential values of a_i.

The artificial ant would update the number of pheromones on the nodes explored by the current rule by depositing pheromones throughout path exploration. The pheromone update of $term_{ij}$ is expressed in Equation 4:

$$\tau_{ij}(t + 1) = \tau_{ij}(t) + \tau_{ij}(t) \cdot Q;\ \forall i, j \epsilon R \tag{4}$$

where,

Q = quality from Equation 2,
R = the set of terms that depend on the rule constructed by the ant at iteration .

The artificial ants utilise a probability function expressed in Equation 5 to select an attribute value for rule generation.

$$P_{i,j} = \frac{HD_{ij}\tau_{ij}}{\sum_{i=1}^{a} x_i\ \cdot\ \sum_{j=1}^{b}(HD_{ij}\tau_{ij}(t))} \tag{5}$$

where,

HD_{ij} = the value of a heuristic function for $term_{ij}$,

τ_{ij} = the amount of pheromone associated with $term_{ij}$ at time t,

a = the total number of attributes,

b_i = the number of values in the domain of the ith attribute,

x_i = set to one if the attribute A_i was not yet utilised by the current ant; otherwise, it was zero.

Dataset Description

The present study conducted two experiments. The first experiment tested the HD-AntMiner algorithm on a publicly available Waikato Environment for Knowledge Analysis (WEKA) dataset. The dataset contained various IRs, from 29.72 percent to 44.49 percent. The Breast-w data have the highest instances at 699 while the Breast-cancer data have the lowest instances at 286 (see Table 1). The second experiment involved 759 Shariah-compliant securities companies in Malaysia, which were recorded from 2000 until 2021. The Shariah-compliant securities company dataset is obtained from the Bursa Malaysia website and the Eikon database. The dataset comprised 13 Malaysian sector types with 34 attributes. The highest number in the dataset was from the industrial products and services sector, with 237 companies. Meanwhile, the lowest number was from the real estate investment trusts sector, which had only four companies. Table 2 depicts the number of bankrupt and non-bankrupt companies for each sector, while Table 3 shows the dataset's attributes list.

Table 1

Descriptions of the Employed Public Datasets

Data	Majority Class	Minority Class	Size	Imbalanced Ratio (%)
Breast-cancer	201	85	286	29.72
Breast-w	458	241	699	34.48
Colic	232	136	358	37.99
Credit-a	383	307	690	44.49
Credit-g	700	300	1000	30

Table 2

Descriptions of the Shariah-compliant Securities Company Dataset

Sector	Bankrupt Companies	Non-bankrupt Companies	Number of Companies
Construction	11	50	61
Consumer Products and Services	28	128	156
Energy	8	22	30
Healthcare	1	13	14
Industrial Products and Services	55	182	237
Plantation	2	34	36
Property	12	87	99
Technology	5	39	44
Telecommunications and Media	3	13	16
Trading and Services	25	0	25
Transportation and Logistics	3	24	27
Real Estate Investment Trusts	0	4	4

Table 3

The List of the Attributes in the Shariah-compliant Securities Company Dataset

Attribute	Name
A1	Sector
A2	Gross Margin
A3	EBITDA Margin
A4	Operating Margin
A5	Pretax Margin
A6	Effective Tax Rate
A7	Net Margin
A8	Asset Turnover
A9	Pretax Margin
A10	Pretax Return On Assets
A11	Leverage (Assets To Equity)

(continued)

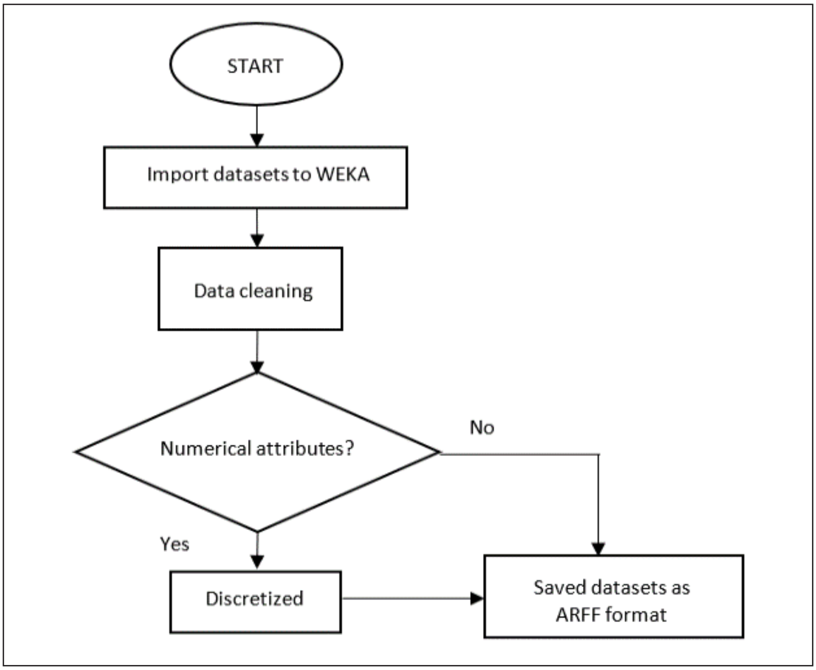
Attribute	Name
A12	Pretax Return on Equity (ROE)
A13	Tax Complement
A14	ROE
A15	Earnings Retention
A16	Reinvestment Rate
A17	Quick Ratio
A18	Current Ratio
A19	Times Interest Earned
A20	Cash Cycle (Days)
A21	Assets/Equity
A22	Capital Structure
A23	Leverage (Long-Term Debt to Total Capital)
A24	(Total Debt – Cash) / EBITDA
A25	Account Receivable Turnover
A26	Average Account Receivable Days
A27	Inventory Turnover
A28	Average Inventory Days
A29	Average Accounts Payable Days
A30	Fixed Asset Turnover
A31	Working Capital Turnover
A32	Bad Debt Allowance
A33	Return On Invested Capital
A34	Status

*EBITDA stand for Earnings Before Interest, Taxes, Depreciation, and Amortisation.

The data pre-processing process commenced by importing the dataset to the WEKA. Subsequently, the dataset underwent data cleaning to remove the error, namely, “Not Applicable (N/A)” responses. The proposed algorithm could handle only nominal attributes, similar to the ACO algorithm. The minimum description length (MDL) algorithm discretised all numerical attributes in the dataset (Fayyad & Irani, 1993). Supervised and unsupervised discretised filters are available in the WEKA. In this study, we applied the discretised supervised approach due to the optimal organisation among the distribution of classes for each attribute. Figure 3 depicts the entire data pre-processing flow.

Figure 3

The Pre-processing of Public Datasets



RESULTS AND DISCUSSION

The present section discusses the effectiveness of the HD-AntMiner algorithm validated through two experiments. The purpose of the first experiment is to evaluate the proposed algorithm on an existing public dataset and compare it with other available methods. The second experiment is to monitor the performance of the proposed algorithm on the Shariah-compliant securities companies dataset and compare it with the original Ant-Miner. This study assessed the performance through prediction accuracy, the number of rules, the number of conditions, the Friedman test, the F-score, and a t-test. According to Parpinelli et al. (2000), the performance of the Ant-Miner focuses on two criteria, namely the prediction accuracy and the simplicity of the discovered rule. The simplicity of the discovered rules consists of the number of rules and the number of conditions. The Friedman test is a non-parametric test to compare three or more matched groups (Scheff, 2016), which is suitable for multiple comparisons between algorithms to rank the highest performer to the lowest performer (Trawinski et al., 2012). The current study conducted the Friedman test through the Knowledge Extraction based on Evolutionary Learning (KEEL) software (Triguero et al. 2017).

Meanwhile, F-scores employ the harmonic mean to combine two classification algorithm performance characteristics: recall and precision (Hand et al., 2021). The F-score ranges from 0 to 1, with 1 as the highest value. The current calculation for precision, recall, and F-scores utilised values from the confusion matrix of the test set (see Table 4).

The total number of test set cases was a combination of the True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN). The formulas of precision, recall, and F-scores are represented in Equations 6, 7, and 8, respectively. Moreover, a t-test was employed to compare the means between the two groups. No significant difference would be discovered between the means of the two groups when the p-value exceeds 0.05 unless the p-value is under 0.05. This study conducted the t-test using the Konstanz Information Miner (KNIME) software (Berthold et al., 2008). In both experiments, this study ran Ant-Miner and HD-AntMiner with the default parameter values, setting the number of ants to five, the minimum cases per rule to five, the maximum uncovered cases to 10, and the convergence rules to 10. The following subsections explain both sets of experimental results.

Table 4

Confusion Matrix

		Predicted	
		Positive (+)	Negative (-)
Actual	Positive (+)	TP	FN
	Negative (-)	FP	TN

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

$$F - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{8}$$

Experiment 1

This study compared the performance of the proposed algorithm with existing algorithms, namely PART, J48, and Ant-Miner. Table 5 depicts the prediction accuracy result on the public dataset, where the highest accuracy for each dataset is bolded. Mainly, this study identified HD-AntMiner as a competent algorithm with the highest accuracy for Breast-cancer, Colic, Credit-a, and Credit-g datasets. The accuracy of HD-AntMiner on Breast-w data was not the highest, as J48 achieved accuracy slightly higher than HD-AntMiner at 94.99 percent. Subsequently, this study appraised the accuracy results for significant differences using the Friedman test. Table 6 depicts the result of the average rank for all algorithms. Specifically, the HD-AntMiner algorithm achieved an average rank of 1.3 on the public dataset. HD-AntMiner comprised the highest number of minority class predictions, which suggested that the algorithms perform optimally in predicting imbalanced datasets compared to the PART, J48, and Ant-Miner. Table 7 shows the F-scores for predictive accuracy, where the highest F-score for each dataset is bolded. The HD-AntMiner algorithm achieved the highest F-score on Breast-cancer and Credit-g data at 0.726 and 0.831, respectively. Comparatively, J48 obtained the highest F-score on Breast-w, Colic, and Credit-a datasets at 0.950, 0.847, and 0.872 respectively.

Table 5

Public Dataset Accuracy

Data	PART (%)	J48 (%)	Ant-Miner (%)	HD-AntMiner (%)
Breast-cancer	71.33	75.52	73.81	**75.64**
Breast-w	94.71	**94.99**	94.85	94.85
Colic	83.97	85.05	81.44	**85.31**
Credit-a	86.38	87.25	85.51	**87.83**
Credit-g	71.90	72.10	71.30	**72.80**

Table 6

The Average Rank from the Friedman Test

Algorithm	Average Rank
PART	3.4
J48	1.8
Ant-Miner	3.5
HD-AntMiner	1.3

Table 7

Public Dataset F-scores

Data	PART	J48	Ant-Miner	HD-AntMiner
Breast-cancer	0.680	0.713	0.701	**0.726**
Breast-w	0.947	**0.950**	0.849	0.844
Colic	0.836	**0.847**	0.780	0.802
Credit-a	0.864	**0.872**	0.748	0.748
Credit-g	0.712	0.710	0.804	**0.831**

Experiment 2

In this study, the proposed HD-AntMiner algorithm compared the bankruptcy data among Shariah-compliant securities companies with the Ant-Miner algorithm. The comparison results in terms of prediction accuracy, namely accuracy, the number of rules, and the number of conditions, are presented in Tables 8, 9, and 10, respectively. The HD-AntMiner achieved higher accuracy than Ant-Miner, although the rules and conditions in both algorithms were equivalent. This study compared Ant-Miner and HD-AntMiner for significant differences through a t-test, and Table 11 depicts the findings. The results revealed that the accuracy p-value was 0.0111, which suggested rejecting the null hypothesis.

Meanwhile, the p-value for the number of rules was 0.6885, and the p-value for the number of conditions was 0.2752, which suggested statistical insignificance and accepted the null hypothesis. The performance of the HD-AntMiner algorithm was also compared with Ant-Miner in terms of the F-score (see Table 12). Kumar and Kaur (2021) stated that the F-score is a more important performance indicator compared to accuracy. The HD-AntMiner achieved a higher F-score than Ant-Miner in the dataset's first, second, third, and fifth years with respective scores of 0.8647, 0.8084, 0.8069, and 0.7596. Nevertheless, the F-score rate of the HD-AntMiner is slightly lower than Ant-Miner in the fourth year. Based on the results, HD-AntMiner produced significantly more accurate findings than Ant-Miner.

Table 8

Comparison of Accuracy

Data	Ant-Miner (%)	HD-AntMiner (%)
1st	83.66	84.98
2nd	81.15	82.88
3rd	82.47	85.77
4th	82.48	83.41
5th	81.68	83.40

Table 9

Comparison between the Number of Rules

Data	Ant-Miner	HD-AntMiner
1st	8.6	8.8
2nd	8.3	8.3
3rd	7.3	7
4th	8.7	8.5
5th	8	8.1

Table 10

Comparison Between the Number of Conditions

Data	Ant-Miner	HD-AntMiner
1st	11.1	10.7
2nd	11.4	12.3
3rd	10.4	10.7
4th	13.1	12.8
5th	10.6	9.8

Table 11

Comparison Between Paired T-tests

Comparison	p-value	Significance
Accuracy	0.0111	
Number of rules	0.6885	
Number of Conditions	0.8501	

Table 12

Comparison of F-scores

Data	Ant-Miner	HD-AntMiner
1st	0.8079	0.8647
2nd	0.6933	0.8084
3rd	0.7802	0.8069
4th	0.7960	0.7797
5th	0.7033	0.7596

The empirical findings of this study emphasize the effectiveness of the HD-AntMiner algorithm, particularly within the domain of Shariah-compliant securities bankruptcy prediction. The enhanced predictive accuracy and F-score of HD-AntMiner, as demonstrated in both public and specialized datasets, can help to improve decision-making processes for financial institutions. By successfully addressing the challenges posed by imbalanced datasets, this algorithm allows for more sensitive and reliable assessments of bankruptcy risk. The implications of this study are far-reaching, offering a potential for reducing financial missteps due to inaccurate predictions and contributing to the stability and integrity of the Islamic financial system.

CONCLUSION

This paper proposed an enhanced ACO algorithm by incorporating the Hellinger distance as the heuristic of ants to address the bankruptcy prediction of Shariah-compliant securities companies and the imbalanced dataset issue. This study conducted the first experiment, testing five publicly available datasets with an IR range from 29.72 percent to 44.4 percent, and compared the results using the Friedman test and F-scores with the PART, J48, and Ant-Miner algorithms. Subsequently, the second experiment was conducted on a bankruptcy dataset of Shariah-compliant securities companies and compared with Ant-Miner using t-test and F-scores. Resultantly, HD-AntMiner outperformed Ant-Miner in terms of accuracy, although the numbers of rules and conditions in both algorithms were equivalent to one another. Future academicians could extend the current research scope by experimenting with more highly imbalanced datasets and a different perimeter setting and applying the proposed algorithms to other bankruptcy datasets. In addition, integrating the algorithm with other computational intelligence techniques, such as deep, could potentially lead to groundbreaking improvements in predictive accuracy.

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