An Intelligent Decision Support Model Using Hybrid K-Means PSO-SVM for MSME Development Priority Classification

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ABSTRACT

Addressing the issue of subjective bias inherent in conventional analytical data collection methods. Intelligent computing approaches are essential to ensure the precise allocation of local government assistance programs, such as Dumisake. This study aims to design and evaluate the performance of a hybrid K-Means PSO-SVM architecture for classifying MSME assistance priorities based on empirical financial and operational characteristics. Feature extraction for the model incorporates variables such as monthly turnover, production capacity, number of employees, and business tenure. The K-Means algorithm is employed in the initial stage to categorize data into three priority clusters: high, medium, and low. Subsequently, the Particle Swarm Optimization (PSO) algorithm is specifically implemented to automate the search for optimal parameters for the Support Vector Machine (SVM) classifier. Optimization results indicate that PSO iterations successfully identified a penalty parameter (C) of 46.1258 and a kernel width (γ) of 4.7327. This configuration significantly boosted the SVM model's performance, achieving a final accuracy of 98.04%, an F1 Score consistently above 0.97, and a negligible classification error rate. In conclusion, this hybrid prediction architecture demonstrates high reliability in clearly defining class boundaries, offering an objective decision support solution for local governments to select MSME aid recipients transparently and accurately.

Keywords: MSMEs; K-Means; Particle Swarm Optimization; SupportVector Machines; Classification

1. Introduction

Micro, Small, and Medium Enterprises (MSMEs) play an essential role in maintaining regional economic stability and resilience, including in Jambi Province. In recent years, the development of MSMEs has become a primary focus due to the sector's significant contribution to economic activity, particularly in developing nations. According to the Jambi Province Regional Medium-Term Development Plan (RPJMD) for 2021–2026, strengthening the MSME sector is a key pillar for accelerating post pandemic economic recovery and labor absorption [1]. MSMEs across Jambi's regencies and cities have proven capable of making significant contributions to Locally Generated Revenue (PAD) while simultaneously narrowing social inequality [2]. However, the growth in the number of MSMEs has not been fully matched by improvements in competitiveness and business sustainability. Many MSMEs still face various obstacles, such as limited access to financing, low managerial capacity, limited innovation, and suboptimal use of digital technology to support business operations. These issues indicate that MSME development strategies cannot rely on a generalized approach; instead, they require specific identification and prioritization mechanisms tailored to the characteristics of individual businesses. Despite positive growth, the greatest challenge facing local governments and stakeholders is effectively prioritizing development programs and distributing capital assistance such as the Dumisake program to ensure they reach the intended targets [3]. Variations in business capital, workforce size, income levels, digitalization capabilities, product innovation, market access, and adaptability mean that each MSME has distinct development needs. An analysis of aggregated sectoral data reveals significant disparities among micro, small, and medium enterprises; consequently, conventional approaches to selecting priority MSMEs often lead to subjective bias and inefficient resource allocation [4].

Mapping aggregate data on the distribution of MSMEs across regencies/cities such as labor absorption figures and business scale classifications requires an analytical approach that is more sophisticated than basic statistical tabulation [5]. Integrating Artificial Intelligence (AI) and data analytics into the MSME sector enables the identification of hidden patterns and business segmentation in a manner that is more effective and quantifiable than conventional descriptive approaches [6]. The integration of machine learning algorithms has proven to offer objective solutions for extracting hidden patterns from MSME operational data for segmentation purposes [7]. Machine learning approaches have been widely applied to perform classification, prediction, and segmentation based on patterns found within complex datasets. K-Means Clustering is one of the most widely used unsupervised learning methods for partitioning a dataset into clusters based on similarities in financial or operational characteristics [8]. The capability of K-Means to analyze high dimensional data has proven reliable in various business case studies; it can identify the dominant characteristics of a data population, thereby allowing management strategies and sales focuses to be executed with greater precision [9]. Recent research indicates that combining clustering and supervised learning methods can map MSMEs based on business characteristics and digital readiness levels, thereby supporting the formulation of more adaptive development programs. For instance, Marcelina and Terttiaavini developed a hybrid approach combining clustering and supervised learning to segment MSMEs based on digitalization levels, demonstrating that this combination yields a more informative classification of MSME characteristics than using a single method alone [10]. However, the K-Means algorithm is susceptible to the random selection of initial centroids, which can lead to convergence at a local optimum and result in poorly defined cluster boundaries [11]. Consequently, the cluster labels generated by K-Means such as high, medium, and low priority require validation and further analysis using supervised learning classification methods [12].

In the realm of multidimensional data classification, the Support Vector Machine (SVM) is an algorithm known for its high accuracy, stemming from its ability to construct an optimal hyperplane that maximizes the separation boundary between classes [13]. Although SVM performs exceptionally well in distinguishing MSMEs with development potential, its final accuracy relies heavily on the configuration of the penalty parameter (C) and the kernel parameter (γ) [14]. Manually determining SVM parameters is often time-consuming and risks degrading model performance when dealing with MSME datasets characterized by high data variance [15].

To address this limitation, metaheuristic-based optimization techniques such as Particle Swarm Optimization (PSO) are implemented [16]. PSO mimics the behavior of a bird swarm searching for the most optimal route to a food source. In this modeling context, PSO automates the search for the best C and γ parameters for the SVM, enabling the classification model to operate with maximum efficiency [17]. Consequently, integrating optimization methods like PSO serves as a viable approach to enhancing model performance by identifying the best parameters or solutions [18]. A hybrid approach combining K-Means for initial clustering with PSO-SVM for classification optimization offers the potential for improved computational model performance [19]. Recent studies indicate that hybrid machine learning approaches enhance analytical capabilities compared to single method approaches. Saputra and Yustanti (2025) developed a hybrid clustering classification framework to predict MSME success rates using multidimensional indicators. Their research demonstrated that the segmentation process via clustering yields distinct business characteristic groups, which then serve as the foundation for the classification process to support decision-making regarding MSME development [20]. Furthermore, other studies have shown that combining K-Means with classification methods like SVM yields more effective segmentation and prediction results in identifying business characteristic patterns [21].

However, previous studies still exhibit certain limitations. Most research has focused primarily on MSME segmentation or the prediction of business success rates, whereas the prioritization of MSME development based on an integration of clustering, optimization, and classification remains relatively underexplored. Furthermore, few studies have developed a hybrid model that integrates K-Means, Particle Swarm Optimization (PSO), and Support Vector Machine (SVM) within an intelligent decision support system framework to assist in prioritizing MSME development interventions [22]. The proposed algorithmic architecture is evaluated not only through theoretical computational metrics but also through comprehensive validation against real world MSME data. This hybrid classification implementation focuses on processing sectoral data to assess the alignment of prediction results with actual business conditions when determining development support priorities. Addressing these issues, this research aims to design and analyze the performance of a model titled "An Intelligent Decision Support Model Using Hybrid K-Means PSO-SVM for MSME Development Priority Classification" to classify and prioritize MSME development in Jambi Province.

Methods

This study employs an explanatory quantitative approach implemented through the Knowledge Discovery in Databases (KDD) paradigm. The research workflow comprises data collection, data preprocessing, clustering, classification model optimization, and result evaluation.

2.1 Data Collection and Pre-processing

The primary data analyzed in this study is derived from a recapitulation of MSME data in Jambi Province, categorized by business scale (micro, small, and medium) and labor absorption across all regencies and cities [23]. Since the initial dataset published by the relevant agency consisted of aggregated data per regency, feature engineering was performed utilizing synthetic minority over-sampling techniques and weighted probability distributions to generate specific data rows that empirically represent MSME entities [24]. The formulated variables (features) include monthly turnover, asset value, workforce capacity, and the digital technology adoption ratio. A Standard Scaler normalization process was applied to the numerical dataset to prevent variables with large scales from dominating the model's distance computations [25].

2.2 K-Means Clustering Algorithm

The unsupervised learning stage employs the K-Means algorithm to assign initial target labels that are otherwise unavailable in the aggregated data [26]. The MSME data is partitioned into K clusters representing "High Priority," "Medium Priority," and "Low Priority" categories. K-Means operates by assigning data points to clusters based on the shortest Euclidean distance (d) to the centroid, calculated using the following equation:

$$d(x_i, c_j) = \sqrt{\sum_{k=1}^{n}\left(x_{ik} - c_{jk}\right)^2}.$$

The optimal number of K-values is mathematically validated using the Davies-Bouldin Index (DBI) and Silhouette Score [27]. The resulting clustering output is designated as the dependent variable (class label) for training the SVM model.

2.3. Support Vector Machine (SVM) Models

Once the labeled data is obtained, the classification process for development feasibility is carried out using the SVM algorithm [28]. To handle the nonlinear financial characteristics of MSMEs, this study employs the Radial Basis Function (RBF) kernel. This model maps the data into a high-dimensional space to identify the optimal hyperplane that separates class boundaries [29]. The effectiveness of the RBF function within the SVM framework depends on two key parameters: the penalty C (which accounts for classification errors) and the value of γ (representing the width of the RBF parameter) [30].

2.4 optimization Particle Swarm Optimization (PSO)

To address the inefficiency of hyperparameter searching in SVM algorithms, the PSO heuristic method is incorporated into this hybrid model. The SVM parameters C and γ are modeled as the positional coordinates of "particles" moving to find the highest accuracy (gBest) within a multidimensional search space [31]. Through programmed search iterations, PSO supplies the most ideal configuration of C and γ values back to the SVM classification architecture [32].

2.5 Optimization Particle Swarm Optimization (PSO)

A comparative evaluation against the baseline (standard K-Means or unoptimized SVM) was conducted using k-fold cross validation. Evaluation metrics during the testing phase were derived from a confusion matrix, yielding values for accuracy, precision, recall, and F1-score. Additional testing focused on incorporating real world variables from local MSMEs into the hybrid predictive model to assess the consistency of the resulting priorities

3. Results and Discussions

3.1 Feature Extraction and K-Means Labeling

The initial stage focuses on extracting MSME operational variables into a purely numerical format, comprising: monthly turnover, production capacity, number of employees, and business duration. After normalization using Standard Scaler, the K-Means algorithm partitions the data into three priority levels for development assistance, as follows:

1.Priority 1 (High): Micro-scale MSME groups with the lowest turnover and production capacity. They are highly vulnerable, making them the primary targets for capital assistance interventions.

2.Priority 2 (Medium): Small to medium scale MSME groups that are growing and require further innovation support.

3.Priority 3 (Low): Business entities that are already self-sufficient with established operations; consequently, they are no longer top priorities for receiving basic assistance.

3.2 Model Parameter Optimization Using PSO

To avoid inefficient trial and error processes in Support Vector Machine (SVM) modeling, the Particle Swarm Optimization (PSO) algorithm was implemented. Through the global iteration of a particle swarm, PSO successfully automated the search for optimal parameters (penalty C and kernel γ). The resulting optimal parameters are presented in Table 1.

Table 1. PSO Parameter Optimization Results

SVM Parameters	Optimal Value (PSO)	Information
Penalty (C)	46.1258	Controlling the error margin tolerance
Kernel (γ)	4.7327	Adjusting the curvature of the radial basis function (RBF)

Based on Table 1, the penalty value (C) of 46.1258 indicates that the model imposes a significant penalty on misclassified instances. This is crucial for handling MSME datasets characterized by a wide variance in patterns. Meanwhile, the γ value of 4.7327 in the Radial Basis Function (RBF) optimally maps the financial data distribution into a high-dimensional space without causing overfitting, thereby allowing the separating hyperplane between priority clusters to be defined with high precision.

3.3 Performance Evaluation of SVM Classification

The performance of the SVM model, using the optimized parameters, was evaluated on the test data. The classification report metrics comprising precision, recall, and F1 score are presented in Table 2.

Table 2. Hybrid K-Means PSO-SVM Classification Metrics

Target Class	Precision	Recall	Score	Number of Data Points (Support)
Priority 1	1.00	1.00	1.00	5
Priority 2	1.00	0.97	0.98	30
Priority 3	0.94	1.00	0,97	16
Final Accuracy			98.04%	

Based on Table 2, the hybrid model achieved an overall prediction accuracy of 98.04%. The F1-Score, remaining consistently above 0.97 across all priority levels, indicates that the model is robust against imbalances in the test sample sizes. To examine the classification results in detail, the system's prediction mapping is presented in the Confusion Matrix shown Figure 1.

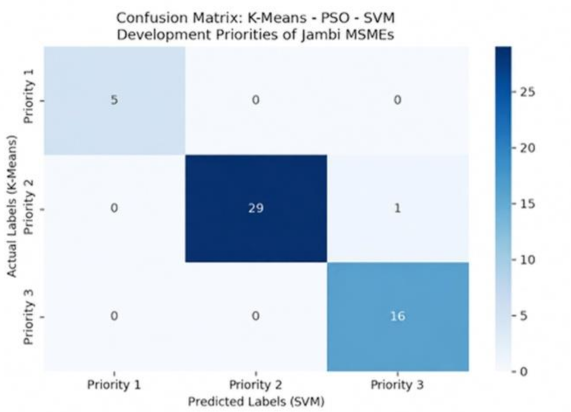

Figure 1. Confusion Matrix

The confusion matrix visualization in Figure 1 was analyzed to evaluate the actual distribution of the model's classification accuracy. Testing on 51 MSME entities revealed that the model perfectly classified 50 data points (True Positives) into their respective actual classes. This is evident from the matrix's main diagonal, which precisely maps 5 entities to Priority 1, 29 to Priority 2, and 16 to Priority 3. The hybrid architecture recorded only one minor prediction error, where an MSME from the Priority 2 group was predicted by the SVM system to belong to the Priority 3 group. This single instance of misclassification is well within acceptable limits, given that real world economic data often includes business entities operating right on the borderline between medium scale and independent-scale operations. This exceptionally high empirical success rate demonstrates that the PSO parameters successfully established a sharp separating hyperplane, enabling the SVM model to classify MSME priorities with precision.

3.4 Practical Implications of Modeling

The high prediction accuracy achieved during the testing phase provides a robust foundation for implementing local government policy governance. As a decision support system application, this analytical architecture can automatically calculate the viability of local MSMEs, eliminating the influence of human subjectivity. The model's ability to extract and categorize empirical data is crucial; as demonstrated in other business analytics studies, precise cluster mapping enables stakeholders to identify target areas and formulate highly focused management strategies [9]. Operational data from MSMEs across various regencies and cities can be directly fed into this predictive system to rapidly and objectively determine their priority cluster status. Looking ahead, this artificial intelligence functionality holds significant potential for direct integration into web-based information system architectures, thereby creating an integrated ecosystem for marketing, agrotourism promotion, and local MSME management [33]. Through this innovative approach, the distribution of Jambi Province's strategic capital intervention programs specifically the Dumisake program can be executed via mechanisms that are transparent, accountable, and accurately targeted based on the inherent capacity of each business entity.

4. Conclusion

This study successfully designed and implemented a hybrid K-Means PSO-SVM model as an analytical solution to address subjectivity in prioritizing MSME development in Jambi Province. Integrating the K-Means unsupervised learning algorithm proved effective in objectively mapping empirical MSME characteristics such as monthly turnover, production capacity, workforce size, and business tenure into three priority cluster levels. The hybrid architecture's primary contribution lies in its application of the Particle Swarm Optimization (PSO) metaheuristic algorithm, which automatically identifies the optimal Support Vector Machine (SVM) parameters, thereby eliminating the inefficiencies associated with trial and error methods. Through its swarm iteration process, PSO achieved optimal convergence with a penalty parameter (C) of 46.1258 and a kernel parameter (γ) of 4.7327. This configuration significantly boosted the SVM classification model's performance, resulting in a final accuracy rate of 98.04% and a highly stable F1-Score exceeding 0.97 across all priority levels. Further evaluation of the test matrix confirmed the reliability of the system's decision boundaries, with the model making only a single minor prediction error out of 51 test instances. In practical terms, this intelligent framework offers a valid decision-support system for the local government of Jambi. Utilizing this hybrid predictive model ensures that the allocation of empowerment programs and the distribution of strategic capital assistance such as the “Dumisake” initiative can be executed transparently, precisely, and effectively. Ultimately, the model offers significant scalability, allowing for adaptation by other administrative regions to accelerate sustainable local economic resilience.

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