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Artificial intelligence-based risk assessment in agro-industry using supervised neural networks

Imam Santoso[1], Izzum Wafi'uddin[1], Naila Maulidina Lu'ayya[1], Annisa'u Choirun[2], Siti Asmaul Mustaniroh[1], Dodyk Pranowo[1], Ainur Rofiq[3]
[1]Department of Agroindustrial Technology, Faculty of Agricultural Technology, Universitas Brawijaya, Malang, Indonesia
[2]Food Engineering Technology Study Program, Department of Agricultural Technology, Politeknik Negeri Jember, Jember, Indonesia
[3]Department of Management, Faculty of Economics and Business, Universitas Brawijaya, Malang, Indonesia

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ABSTRACT

The coffee supply chain involves high production volumes, complex multi-actor interactions, and increasing sustainability requirements, yet remains highly vulnerable to risks dimension. This study aims to develop and evaluate a decision-support framework that improves the accuracy and consistency of sustainability risk classification in the coffee supply chain. The proposed framework integrates failure mode and effect analysis (FMEA) with a supervised artificial neural network (ANN) using backpropagation (BP) to enable data-driven and adaptive risk assessment. Empirical data was collected from 55 respondents, resulting in the identification of 35 supply chain risk factors. These data were used to train and validate an ANN-based classification model implemented in a Python environment, with standard preprocessing and stratified data partitioning to ensure robustness. The ANN classified risks into five categories using supervised learning. The results demonstrate strong predictive performance, achieving overall accuracy of 98.97%, with precision, recall, and F1-scores exceeding 96.8% across all risk classes. Confusion matrix analysis confirms reliable generalization and minimal misclassification. The findings indicate that integrating FMEA with ANN-BP significantly enhances risk classification compared to conventional qualitative approaches. The proposed framework provides a scalable and reliable decision-support tool for dynamic risk scoring, supporting enhancement of sustainable practices in agro-industrial coffee supply chains.

Corresponding Author:

Imam Santoso
Department of Agroindustrial Technology, Faculty of Agricultural Technology, Universitas Brawijaya
10-11 Veteran St., Ketawanggede, Lowokwaru, Malang 65145, East Java, Indonesia
Email: imamsantoso@ub.ac.id

1. INTRODUCTION

Artificial intelligence (AI) has emerged as a transformative force across diverse sectors. Its implementation has revolutionized industries by enabling real-time data analysis, pattern recognition, prediction, thereby supporting more intelligent decision-making [1]–[4]. In the agroindustrial sector marked by seasonality, multi-actor networks, and high levels of uncertainty AI has the potential to transform conventional processes by promoting efficiency, resilience, and sustainability [1], [5], [6]. Scholars and practitioners alike have increasingly acknowledged the value of AI in optimizing agricultural production [7], improving quality control [8], and strengthening supply chain performance [9]–[13].

Coffee represents a strategic agro-industrial commodity for Indonesia, with an estimated annual production of approximately 774,960 tons distributed across several key provinces [14]. Despite the economic potential of the coffee industry, its supply chain is increasingly exposed to several systemic risks. Agri-food supply chains are particularly susceptible to a range of risks, including fluctuating demand, seasonality, price volatility, and external environmental disruptions [15], [16]. These factors contribute to increased uncertainty and elevate both the likelihood and severity of risk events across the supply chain [15]. A study by the International Coffee Organization (ICO) reports that unsustainable practices in the coffee supply chain result in waste equivalent to 20% of total production, leading to an estimated financial loss of $10 billion annually for the industry. Although integrating sustainability into supply chain management is imperative, it introduces additional complexity that challenges traditional decision-making models [15].

To address these multifaceted problems, numerous studies have proposed decision support mechanisms that integrate sustainability considerations into supply chain risk management. failure mode and effect analysis (FMEA) is a widely applied risk management approach used to systematically identify potential risk events and evaluate their potential impacts across various industrial domains [16], [17]. Integrating FMEA with AI enhances the efficiency and accuracy of supply chain risk evaluation. Integrating FMEA with AI enhances the efficiency and accuracy of supply chain risk evaluation by enabling faster, more objective, and data-driven decision-making. In this study, the AI technique employed is the artificial neural network (ANN), which is particularly well-suited for handling the complexity and uncertainty inherent in supply chain environments [18]–[21]. This integration allows for dynamic and scalable risk scoring, reduces subjectivity, and supports continuous learning and improvement, ultimately strengthening the responsiveness and reliability of supply chain risk assessments. The objective of this study is to analyze the application of a supervised ANN with backpropagation (BP) as a predictive model for evaluating risks in the coffee supply chain, aiming to enhance the accuracy, consistency, and adaptability of risk assessments in complex and data-intensive environments.

Recent studies have highlighted the growing role of machine learning (ML) and AI in improving risk assessment across various agro-industrial sectors. Paltrinieri *et al.* [22] demonstrated that deep neural networks (DNNs) could support risk management in safety-critical industries by addressing challenges such as dynamic environments and the need for continuous learning. Similarly, Kamyshova [23] showed that neural network models could effectively minimize risks and enhance efficiency in irrigated agriculture by accounting for nonlinear and dynamic system behavior. In context of occupational safety, Kakhki *et al.* [24] applied multilayer perceptron (MLP) and radial basis function (RBF) neural networks to predict the causes of incidents in grain handling facilities, achieving high predictive accuracy and identifying critical risk factors. Additionally, Ghaffarian *et al.* [25] provided a comprehensive review of ML applications in agriculture, emphasizing the use of supervised learning for classification tasks related to various risk types, including production and environmental risks.

Despite these advancements, there remains a gap in the application of ML-based risk classification specifically within the coffee agroindustry, where complex, multidimensional risks persist throughout the supply chain. Existing studies have not sufficiently explored how predictive models can support risk evaluation in this sector, particularly by integrating structured risk assessment frameworks such as FMEA with supervised ANNs. This study addresses this gap by implementing an ANN-BP to classify sustainability-related risks in the coffee supply chain, offering a novel integration of traditional risk assessment (FMEA) with modern AI-based classification. This contribution extends the application of ML in agriculture by focusing on the coffee industry and providing a structured model for enhancing risk evaluation accuracy and decision-making.

2. METHOD

This study adopts two methodological approaches: the experimental method and the data-driven method. The experimental method is used to identify and analyze risks in the coffee agroindustry supply chain, while the data-driven method relies on AI, specifically supervised ANN, to analyze and classify risks. A detailed research method design is presented in Figure 1.

2.1. Experimental method

The experimental method is designed to systematically identify and analyze potential risks affecting the coffee agro-industry. This approach involves both qualitative and quantitative data collection and categorization based on sustainability dimensions. There are several key steps, including as follows:

i) Identification of potential risks: the initial phase involves identifying various risks that may impact the coffee agro-industry. This is achieved through expert consultations, literature reviews, and field observations.

ii) Grouping risks by sustainability aspects: identified risks are categorized into sustainability dimensions such as social, economic, and environmental aspects. This classification facilitates a holistic understanding of the risks' broader implications.
iii) Collection of S-O-D values: for each risk, three critical parameters are measured by 55 respondents. These include severity (S): the potential impact of the risk; occurrence (O): the likelihood of the risk occurring; and detection (D): the probability of detecting the risk before it causes harm.
iv) Calculation of risk priority number (RPN): using the S-O-D values, the RPN is calculated for each risk. The RPN quantifies the criticality of risks, enabling prioritization.
v) Classification of risks based on RPN: risks are then classified into five priority levels according to their RPN scores, guiding targeted risk mitigation strategies. The classification targets are as follows: very low = RPN 1–40; low = RPN 41–100; moderate = RPN 101–200; high = RPN 201–500; and very high = RPN 501–1000. This classification helps in prioritizing risks from least to most critical, allowing for efficient allocation of resources and mitigation efforts [26], [27].

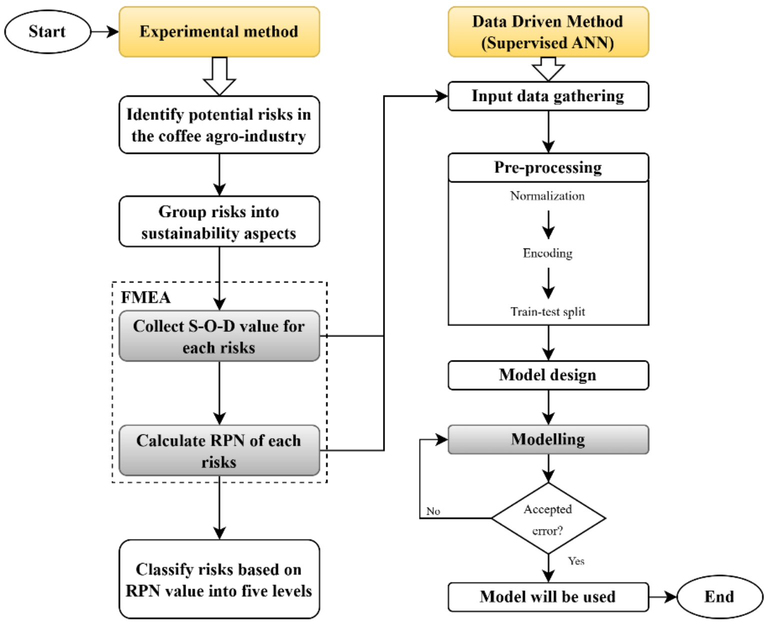


Figure 1. Research method design

2.2. Data-driven method

The data-driven method employed a supervised ANN approach to classify risk categories in the coffee supply chain using a supervised learning framework. The development process consisted of several stages: data pre-processing, model design, training, and evaluation. The model was implemented using the TensorFlow library with the Keras API in Python.

i) Input data gathering: relevant risk-related data are gathered from the coffee agro-industry supply chain and prepared for further analysis. This data serves as the foundation for training the AI model.
ii) Data pre-processing: the raw dataset was first cleaned and prepared for modeling. Categorical variables, including risk categories and specific risk types, were encoded using LabelEncoder. To facilitate multi-class classification, the target variable was transformed into a one-hot encoded format. Numerical features, particularly the RPN, were normalized using the StandardScaler to ensure all features contributed equally during model training. The entire dataset was then split into training (70%), validation (15%), and test sets (15%). This stratified division ensured a balanced representation of each risk category across all subsets.
iii) Model design: the ANN model was constructed using a sequential architecture composed of multiple fully connected (Dense) layers. To enhance training stability and reduce internal covariate shift, BatchNormalization layers were incorporated after dense layers. Additionally, dropout layers were applied to mitigate overfitting by randomly disabling a fraction of neurons during training. The output layer consisted of five nodes corresponding to the five predefined risk categories. A softmax activation

function was applied to this layer to generate a probability distribution across all categories. The class with the highest probability was selected as the final prediction. The network architecture of this research can be seen in Figure 2.

iv) Model training: the model was compiled using the categorical_crossentropy loss function, appropriate for multi-class classification tasks. The Adam optimizer, which internally uses BP, was employed to update weights and biases during training. The default learning rate provided by TensorFlow was used throughout. Model training was conducted with a batch size of 32 over a maximum of 500 epochs. An EarlyStopping mechanism with a patience of 100 epochs was implemented to halt training when the validation loss failed to improve, thereby preventing overfitting. A ModelCheckpoint callback was also used to save the model with the lowest validation loss during training.

v) Error evaluation: following training, the best model was evaluated using the test dataset. The model output, expressed as a vector of probabilities from the softmax layer, was converted to discrete class labels using the argmax function. Model performance was assessed through various metrics, including accuracy, precision, recall, and F1-score, all derived from the classification report. Additionally, a confusion matrix was generated to provide further insight into the model's classification performance across categories. If performance did not meet expectations, several aspects could be revised, including feature engineering, model architecture, or hyperparameter tuning.

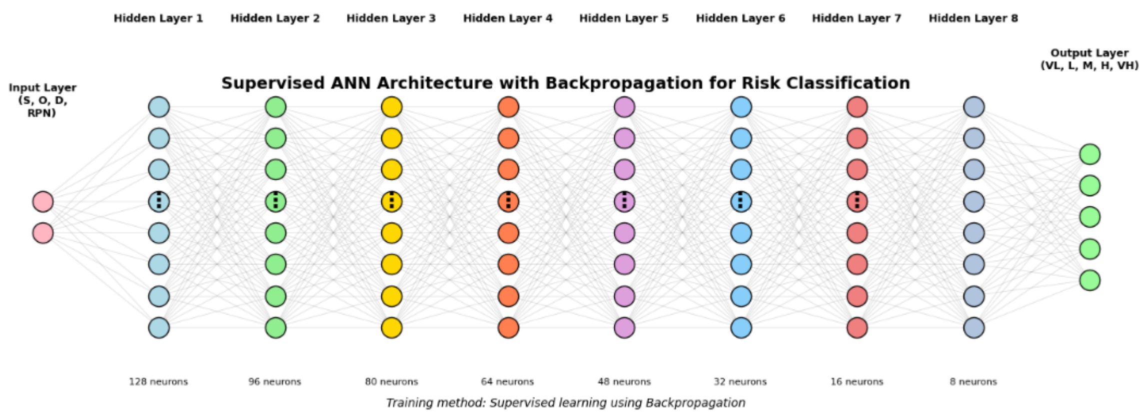


Figure 2. Network architecture ANN

3. RESULTS AND DISCUSSION

3.1. Potential risks in coffee agro-industry

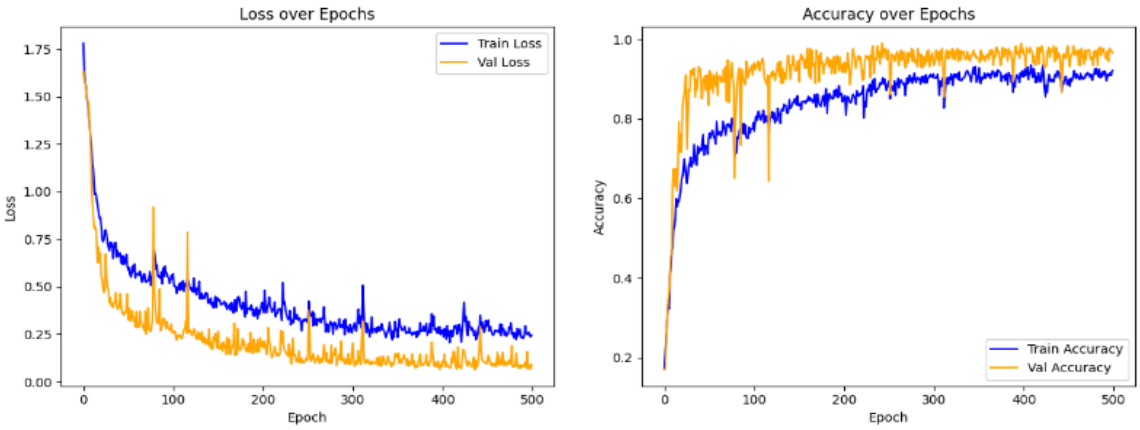
The identification results revealed 35 potential risks within the coffee supply chain; each linked to one or more of seven sustainability dimensions. Social risks relate to the welfare of supply chain actors; economic risks concern financial stability and profitability; environmental risks involve threats to ecosystems and long-term sustainability; technological risks highlight limitations in adoption and infrastructure; operational risks pertain to production and distribution challenges; enterprise risks reflect strategic and managerial issues; and quality risks involve the consistency and compliance of final products. Full details are presented in Table 1. Each identified risk was then encoded with numerical values from 1 to 35. The S-O-D scores, along with the RPN for each risk, are provided in the supplementary file, which served as the dataset for training and evaluating the ANN model. In total, the researcher will obtain 1,925 data sets, consisting of 1,925 S-O-D score combinations for each risk and their corresponding 1,925 RPN values.

3.2. Model training result

Based on Figure 3, the graph of loss over epochs as shown in Figure 3(a) and the graph of accuracy over epochs as shown in Figure 3(b), the training results of the model can be summarized as follows. Prior to training, the dataset underwent pre-processing and was divided into 1,347 training data, 289 validation data, and 289 test data. Initially, both the training loss and validation loss decreased sharply during the first 50 epochs, dropping from approximately 1.7–1.8 to around 0.4–0.6. This indicates that the model quickly learned the fundamental patterns in the data. After epoch 50, training loss continued to decline gradually to around 0.3 by epoch 500, with minor fluctuations likely due to mini-batch gradient descent. The validation loss reached its lowest point (~0.15–0.2) between epochs 100 and 200, then remained relatively stable with no significant upward trend, suggesting that the model did not suffer from severe overfitting.

Table 1. Potential risks in coffee agro-industry

Risk dimension	Code	Risk indicator	Risk ID
Social	S1	Information security and contracts	1
	S2	Government policy changes	2
	S3	Long supply chain	3
	S4	Work accidents	4
Economic	F1	Income uncertainty	5
	F2	High storage costs	6
	F3	Price fluctuations	7
	F4	High transportation costs	8
	F5	Inflation/currency depreciation	9
Environmental	L1	Pest/disease infestation	10
	L2	Unpredictable weather	11
	L3	Waste processing errors	12
	L4	Carbon emissions	13
	L5	Natural disasters	14
	L6	Fires	15
Technology	T1	Poor farming practices	16
	T2	Improper planting techniques	17
	T3	Equipment failure	18
	T4	Raw material damage	19
Operational	O1	Contract non-compliance	20
	O2	Harvesting errors	21
	O3	Uncertain raw material stock	22
	O4	Limited workforce	23
	O5	Raw material delays	24
	O6	Packaging errors	25
Enterprise	E1	High competition	26
	E2	Unstable market demand	27
	E3	Recording errors (purchase/sales)	28
Quality	Q1	Low raw material quality	29
	Q2	Limited technology and innovation	30
	Q3	Poor packaging	31
	Q4	Pest damage to product	32
	Q5	Product rejection	33
	Q6	Variable bean quality	34
	Q7	Quality loss during storage	35



(a) (b)

Figure 3. Graph of (a) loss over epochs and (b) accuracy over epochs

In terms of accuracy, the training accuracy improved from around 20% at epoch 0 to approximately 80% by epoch 100, eventually reaching about 92% by epoch 500. Validation accuracy increased even more rapidly, reaching approximately 90% by epoch 50 and stabilizing between 94–97% after epoch 100. Interestingly, the validation performance slightly exceeded training performance, indicating that the model achieved good generalization and did not merely memorize the training data.

Overall, the model appears to have converged by around epoch 200, with only marginal improvements in loss and accuracy thereafter. Thus, the use of early stopping between epochs 150 and 200 could be considered to reduce computational time without compromising performance. In conclusion, the supervised neural network model demonstrated strong learning and generalization capabilities, achieving approximately 95% validation accuracy and a validation loss of around 0.2.

The performance of the model is further evaluated using a confusion matrix. The confusion matrix for the testing data, as illustrated in Figure 4, indicates that the model successfully classified nearly all samples correctly. Of the 97 class 0 samples, 96 were predicted accurately, with only 1 misclassification. For class 1, 65 out of 66 samples were correctly classified, while 1 sample was misclassified. All 60 class 2 samples were identified perfectly without any errors. In class 3, 52 out of 53 samples were accurately predicted, with just 1 misclassification. Class 4 achieved perfect accuracy, with all 13 samples correctly classified. Based on these results, the precision and recall for each class ranged from 96.8%–100%, and the F1-scores ranged from 0.9848–1.0000. Overall, the model correctly classified 286 out of 289 samples, resulting in a total accuracy of approximately 98.97%. These outcomes demonstrate that the developed supervised neural network has excellent generalization capabilities and is highly reliable in mapping agro-industrial risks. The high accuracy demonstrated by the confusion matrix in this study confirms the model's strong predictive performance, which aligns with findings from previous research highlighting the critical role of accurate classification models in effective decision support systems [23], [28]. Therefore, the model developed here is well-suited for integration into a decision support system to assist in agro-industrial risk management.

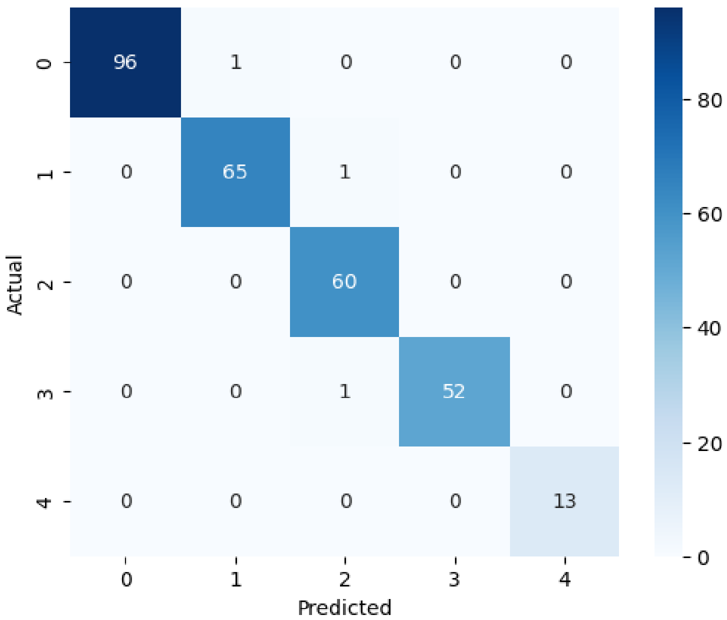


Figure 4. Confusion matrix for the testing data

4. CONCLUSION

This study successfully demonstrated the application of a supervised ANN-BP as an effective predictive model for evaluating risks in the coffee supply chain. The model achieved a high overall accuracy of approximately 98.97%, with precision, recall, and F1-scores consistently above 96.8% across all risk classes. These results confirm the model's strong capability in accurately classifying complex risk categories within a data-intensive environment. The excellent predictive performance indicates that the ANN model is not only reliable but also adaptable for real-world applications. Consequently, this approach holds significant potential for integration into decision support system to improve risk management practices in the coffee supply chain, contributing to more consistent and data-driven risk assessment and mitigation.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Imam Santoso	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓		✓
Izzum Wafi'uddin			✓	✓		✓	✓		✓	✓	✓			
Naila Maulidina Lu'ayya			✓	✓		✓	✓		✓	✓	✓			
Annisa'u Choirun	✓	✓				✓		✓	✓	✓		✓		
Siti Asmaul Mustaniroh	✓	✓	✓	✓			✓		✓	✓		✓		
Dodyk Pranowo	✓	✓							✓	✓		✓		
Ainur Rofiq					✓		✓		✓	✓			✓	

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare no competing interests.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [IS], upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Imam Santoso is a professor and expert in agroindustrial systems and management. He earned his doctorate in Agroindustrial Technology from IPB University in 2005. His expertise includes risk-based analysis, decision support systems, intelligent performance strategies, and strategic planning in agroindustry. He is actively involved in sustainable agroindustrial research and interdisciplinary innovations. Since 2024, he has initiated the development of a research roadmap on artificial intelligence in agroindustrial systems. He can be contacted at email: imamsantoso@ub.ac.id.

Izzum Wafi'uddin received master's degree in Engineering from Universitas Brawijaya, Indonesia, in 2025. His research focuses on lean manufacturing, risk management, operations research, and the development of sub-grade coffee-based products. Recently, he has been concentrating on mathematical modeling for risk management in the agroindustrial sector, including the integration of AI-based methods. He can be contacted at email: izzum_456@student.ub.ac.id.

Naila Maulidina Lu'ayya received her master's degree in Engineering from Universitas Brawijaya, Indonesia, in 2025. Her areas of expertise include risk management, supply chain management, and product development in agroindustry. She has actively contributed to research and development in sustainable management related to agroindustrial system innovation, including the integration of risk management approaches with artificial intelligence. She can be contacted at email: nailamaulidina@student.ub.ac.id.

Annisa'u Choirun earned her master's degree in Engineering from Universitas Brawijaya, Indonesia, in 2020. She is a lecturer in the Food Engineering Technology Study Program at Politeknik Negeri Jember, with expertise in food engineering, production management, and graphic design. Actively involved in both teaching and applied food processing, she contributes to innovation in agro-industrial education. She can be contacted at email: annisa@polije.ac.id.

Siti Asmaul Mustaniroh holds a doctorate in Industrial Manufacturing Engineering from Universitas Brawijaya. She is a lecturer and researcher in agroindustrial systems management, focusing on institutional development and business strategies for both industrial enterprises and micro, small, and medium enterprises (MSMEs). Her interests include supply chain management, quality control, marketing, and strategic planning. She actively engages in community empowerment through applied agroindustrial innovation. Recently, she has begun developing a research roadmap on decision support systems and advanced risk management. She can be contacted at email: asmaul_m@ub.ac.id.

Dodyk Pranowo earned his doctorate in 2016 from IPB University. He is a lecturer and researcher focused on empowering MSMEs in food processing. His research covers sustainable product development, food innovation, value-added agroindustrial processing, and biopharmaceuticals. He is actively involved in developing coffee-based product prototypes and integrating sustainability with machine learning for yield prediction in agroindustry. He can be contacted at email: dodykpranowo@ub.ac.id.

Ainur Rofiq completed his Ph.D. in 2013 at The University of Southern Queensland, Australia. He is an expert in management and digital marketing, with research focusing on digital business strategies, supply chain management, and quantitative decision models. His work supports agroindustrial competitiveness through digital innovation and data-driven management. He can be contacted at email: rofiq@ub.ac.id.