Jurnal Teknologi Industri Pertanian 35 (2): 196-207, August 2025
DOI: https://doi.org/10.24961/j.tek.ind.pert.2025.35.2.196
ISSN: 0216-3160 EISSN: 2252-3901

Terakreditasi Peringkat 2
SK Dirjen Pendidikan Tinggi, Riset, dan Teknologi No. 158/E/KPT/2021
Tersedia online http://journal.ipb.ac.id/index.php/jurnaltin

SYSTEM ANALYSIS AND DESIGN PRODUCTION OF EDIBLE BIOFILM FROM MINT LEAF ESSENTIAL OIL AS AN ANTIMICROBIAL

ANALISIS SISTEM DAN PERANCANGAN PRODUKSI EDIBLE BIOFILM DARI MINYAK ATSIRI DAUN MINT SEBAGAI ANTIMIKROBA

Griselda Happy Ramadhani[1)*], Syifa Robbani[2)], and Ninta Sri Ulina[1)]

[1)]Department of Industrial Engineering, Faculty of Engineering and Computer Science, Indraprasta PGRI University
Jalan Nangka Raya No. 58C Tanjung Barat, South Jakarta, Indonesia, 12530
[2)]Study Program of Agriculture Engineering, Department of Agricultural Technology, Faculty of Agriculture, Universitas Sriwijaya
Jl. Palembang-Prabumulih, KM 32 Indralaya, Ogan Ilir, South Sumatra, Indonesia, 30862
Email : griselda.happyramadhani@unindra.ac.id

Paper: Received April 21, 2025; Revised June 10, 2025; Accepted June 25, 2025

ABSTRAK

Pengemasan yang buruk menyebabkan kerusakan makanan, menurunkan kualitas serta umur simpan produk. Pengemasan aktif menggunakan biofilm yang dengan kandungan minyak esensial antimikroba diketahui mampu menghambat pertumbuhan mikroba dan memperpanjang kesegaran produk. Tujuan dari penelitian ini adalah untuk mengklasifikasikan produk biofilm yang dapat dimakan guna menentukan kualitasnya serta memprediksi kondisi pengeringan yang tepat. Metode yang digunakan melibatkan pemodelan sistem dengan *Unified Modeling Language* (UML) dan *Business Process Model and Notation* (BPMN) untuk memetakan proses produksi mulai dari penanganan bahan baku hingga produksi skala industri. Selanjutnya, diterapkan model machine learning: model *Decision Tree* untuk klasifikasi kualitas produk meliputi sifat fisik, mekanik, dan kemampuan antimikroba, serta regresi linear *Ordinary Least Squares* (OLS) untuk prediksi parameter pengeringan. Langkah penelitian mencakup pembuatan model sistem guna meningkatkan kejelasan dan keselarasan tim, pengumpulan data terkait elongasi, kekuatan tarik, kadar air, dan aktivitas antimikroba, kemudian menerapkan *Decision Tree* untuk klasifikasi kualitas dan kategori aktivitas antimikroba ke dalam empat tingkat. Regresi OLS digunakan untuk memodelkan hubungan antara kondisi pengeringan dan kadar air akhir. Hasil menunjukkan bahwa pemodelan dengan UML dan BPMN meningkatkan pemahaman dan konsistensi alur produksi. *Decision Tree* berhasil mengklasifikasikan kualitas biofilm ke dalam tiga kategori dengan akurasi 80,5% dan kemampuan antimikroba ke dalam empat tingkat dengan akurasi 95%. Model OLS memprediksi hasil pengeringan dengan daya jelas sebesar 64% dan signifikansi statistik (p-value < 0,05). Penelitian ini berkontribusi pada pengembangan kemasan cerdas dengan mengintegrasikan pemodelan sistem dan machine learning, sehingga memungkinkan klasifikasi dan prediksi dini untuk meningkatkan pengendalian mutu, efisiensi, dan keandalan dalam kemasan aktif untuk industri pangan.

Keywords**:** antimikroba, *decision tree, edible biofilm, linear regression, use case*

ABSTRAK

Poor packaging can definitely contribute to food spoilage, reducing food quality and shelf life. Active packaging using edible biofilm with antimicrobial essential oils can inhibit microbial growth and extend product freshness. The purpose of this study was to classify edible biofilm products to determine their quality and predict proper drying conditions. The method involved system modeling using Unified Modeling Language (UML) and Business Process Model and Notation (BPMN) to map the production process from raw material handling to industrial scale manufacturing. Subsequently, machine learning models were applied: the Decision Tree model for classifying product quality including physical, mechanical, and antimicrobial properties and Ordinary Least Squares (OLS) linear regression for predicting drying parameters. The research steps consisted of creating system models to improve clarity and team alignment, collecting relevant data on elongation, tensile strength, moisture content, and antimicrobial activity, then applying the Decision Tree for quality classification and antimicrobial categorization into four levels. OLS regression was used to model the relationship between drying conditions and final moisture content. Results demonstrated that UML and BPMN modeling enhanced understanding and consistency in production flow. The Decision Tree classified edible biofilm quality into three categories with 80.5% accuracy and antimicrobial ability into four inhibitory levels with 95% accuracy. The OLS regression predicted drying outcomes with 64% explanatory power and statistical significance (p-value < 0.05). This study contributes to intelligent packaging development by integrating system modeling and machine learning, enabling early classification a nd drying prediction to improve quality control, efficiency, and reliability in active food packaging.

Keywords: antrimicobe, decision tree, edible biofilm, linear regression, use case

**Coressponding Author*

INTRODUCTION

Food packaging is a crucial tool for preserving the quality and safety of food. The most commonly used food packaging materials are plastics made from polyester and polypropylene, along with variations of other plastic materials. However, many plastic packaging materials are difficult to decompose naturally, leading to the development of alternative materials to replace plastic with biodegradable packaging. One such biodegradable alternative is edible biofilm, a type of plastic that can naturally degrade in the environment (Subroto *et al.,* 2021). Food packaging must consider the product's condition, as poor packaging can negatively impact food product quality. Therefore, a packaging technique called active packaging has been developed. In general, antimicrobial packaging is achieved by incorporating antimicrobial agents into active packaging films with antimicrobial agents, or using polymer-based materials with inherent antimicrobial properties (Irkin and Esmer, 2015). Fresh food products are highly perishable and require proper protection to maintain their quality.

Research by Suwarda *et al.* (2019) emphasized that starch with a high amylose content tends to form edible films with superior thin-layer properties compared to low-amylose starch. Starch-based films are known for their excellent gas barrier properties against O_2 and CO_2, though they typically exhibit poor water vapor resistance due to their hydrophilic nature. Moreover, starch-based edible films show varying levels of stability during storage, which may affect their protective function on food products. This study builds on that foundation by not only utilizing starch as the primary film-forming agent but also enhancing its antimicrobial functionality through the incorporation of essential oils. While Suwarda et al. discussed chemical changes such as protein sulfhydryl oxidation that can degrade polymer chains over time, the current study addresses that limitation by improving film stability and extending shelf life through the functional benefits of essential oils. Starch remains advantageous due to its renewability, biodegradability, affordability, and ability to form strong, flexible films features that are further optimized when combined with bioactive compounds like essential oils.

Edible biofilm packaging combined with essential oils has recently gained attention due to its benefits as active antimicrobial packaging (Karimian *et al.*, 2019). Starch, combined with organic materials and plasticizers, can be used to produce edible biofilms (Subroto *et al.,* 2021). The addition of antimicrobial agents, such as essential oils, to the film helps combat microorganisms, extend shelf life, and maintain food quality and safety. Furthermore, incorporating active compounds such as antioxidants into this coating can enhance its functional properties. Essential oils derived from mint leaves have been investigated for their antimicrobial composition (Nasiri *et al.*, 2019).

Edible biofilm enriched with mint essential oil offers several advantages, including broad-spectrum antimicrobial activity against both Gram-positive and Gram-negative bacteria, strong antioxidant properties, and the ability to enhance the shelf life of fresh food products. The high content of active compounds like menthol and menthone in mint essential oil contributes significantly to its effectiveness in inhibiting microbial growth (Kang *et al.,* 2019). Moreover, the incorporation of mint essential oil into biopolymer-based edible films has been shown to improve mechanical and barrier properties, making the films more suitable for commercial food packaging applications (Ashrafudoulla *et al.,* 2023).

The production of edible biofilms on an industrial scale has not yet been widely implemented and remains limited to laboratory-scale development, as demonstrated in previous studies. Therefore, analyzing and designing an edible biofilm production system is essential to enable large-scale commercialization. Scaling up edible biofilm production requires an industrial approach that involves various stakeholders who interact and collaborate to achieve the final goal. To facilitate stakeholder interaction in this digitalization era, a *systems approach* is applied, with the Digital Business Ecosystem (DBE) serving as the core of business strategy and operations. This ecosystem represents the increasing interconnectedness of businesses and their deepening reliance on digital technology to create value ((Fatmawati and Munajat, 2018). In modern business, competition is no longer confined to individual companies but extends to entire ecosystems where businesses interact, collaborate, and depend on one another (Fatmawati and Munajat, 2018).

In this context, system modeling is conducted using the Unified Modeling Language (UML). Modeling simplifies complex problems, making them easier to analyze and understand (Fatmawati and Munajat, 2018). UML system has been widely used to model the structure and behavior of software systems and is a standard approach in software development for representing and describing system architecture (Nasiri *et al.,* 2019). The edible biofilm production system is modeled using UML through *use case diagrams* and *business process modeling* with Business Process Model and Notation (BPMN). A use case diagram (UCD) represents a system's functionality by illustrating its various users and their interactions to achieve specific goals. It also depicts the business process flow and sequence of activities within the system (Karimian *et al.*, 2019). Meanwhile, BPMN is a tool for simulating the impact of transitioning business processes from manual or traditional methods to digital and integrated approaches, supported by advanced equipment and facilities (Karimian *et al.*, 2019).

In addition, this system is designed to classify edible biofilm products based on their quality and antimicrobial properties using the decision tree model. In addition, this system is designed to classify edible biofilm products based on their quality and antimicrobial properties using the decision tree model. The use of decision tree algorithms in predictive modeling has been proven effective in previous research. For instance, (Ravi and Malathi, 2022) demonstrated that a Novel Decision Tree Regressor outperformed the Linear Regression algorithm in predicting future product prices using Bigmart Sales data, achieving 97.5% accuracy compared to 87.6% for linear regression. Although the prediction may not always be exactly accurate in real-world application, it has shown to provide statistically significant results ($p < 0.05$), supporting better business decision-making strategies. Moreover, the Ordinary Least Squares (OLS) linear regression model is applied to predict optimal drying conditions. This paper discusses the analysis and design of an edible biofilm production system by integrating UML based modeling and machine learning techniques to provide solutions for assessing edible biofilm quality, antimicrobial effectiveness, and optimal drying conditions.

This study on edible biofilm quality classification complements Nurhasanah's (2025) research on institutional system design using Interpretive Structural Modeling (ISM) and system design approaches focused on graphical user interface development. While Nurhasanah's work structures and supports institutional operations, this research provides a practical decision-making model for biofilm production quality. Integrating such classification models into institutional information systems, could enhance operational efficiency and real-time quality control, paving the way for future advancements beyond interface design toward full system integration.

The novelty of this research lies in the integrated approach of combining UML-based system modeling with machine learning techniques specifically decision tree classification and OLS linear regression to design a scalable, digitalized edible biofilm production system enriched with mint essential oil. Unlike previous studies that focused only on laboratory-scale film formulation or single-aspect quality evaluation, this study introduces a comprehensive system that not only models stakeholder interactions and production processes digitally but also embeds intelligent decision support for product classification and drying optimization. By incorporating antimicrobial analysis, mechanical properties evaluation, and predictive modeling into a unified framework, the research bridges the gap between experimental development and industrial-scale application, offering a practical solution for future commercialization and digital transformation of biodegradable packaging production.

RESEARCH AND METHODS

Research Framework and Process Flow

To provide insightful research framework, the steps of this study are outlined in a structured flow chart. This flowchart represents a systematic process that integrates system modeling with predictive analysis. It begins with identifying the problem and conducting a literature review, followed by requirement analysis and system modeling using UML and BPMN. Afterward, data is collected for edible biofilm quality and antimicrobial analysis. The classification of product quality is performed using decision tree algorithms, while OLS linear regression is applied to predict optimal drying conditions. The evaluation of both models is then conducted based on their accuracy, R^2, and significance levels. Finally, the research is concluded with system integration and recommendations for industrial implementation. A predictive model comparison using the Bigmart Sales dataset from Kaggle was also performed to support model evaluation.

Recruitment Analysis and System Modeling

The analysis is conducted to identify system requirements and system-building components. System requirements analysis represents the attributes of a system's construction, including desired and undesired inputs and outputs, stakeholders, roles, resources, internal controls or constraints, opportunities, threats, operating limitations, and reciprocity in the form of self-interaction can be seen Figure 1. These attributes significantly impact system performance, making them essential considerations in system determination, design, and development (Djatna, 2019).

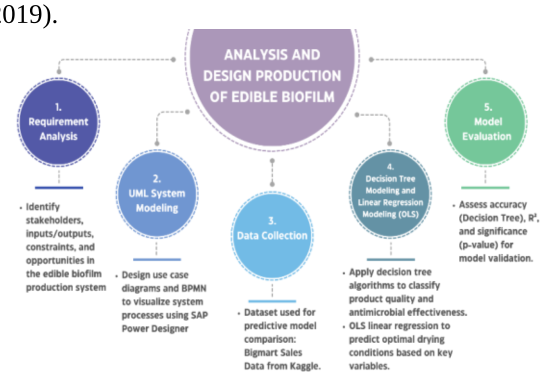

Figure 1. Research steps in edible biofilm system design

In this project, system representation is studied and analyzed in the context of *entity system construction*, referring to the System of Interest (SOI). System modeling is performed using UML with SAP Power Designer 16.0 software (2013). Modeling simplifies complex problems, making them easier to analyze and understand (Fatmawati and Munajat, 2018). The edible biofilm production system is modeled using UML through use case diagram and BPMN.

A use case diagram serves as an effective starting point for understanding and analyzing system requirements during the design phase. It provides a clear representation of the system's processes, the roles of actors interacting with the system, and the functions they can perform (Nisak and Nugraha, 2018). Meanwhile, BPMN represents the business process flow using a standardized set of graphical notations that are easily understood by business professionals, including analysts responsible for creating and optimizing business processes (Yunitarini and Hastarita, 2016).

Formulation System Using Decision Tree

A decision tree is used to classify the resulting product's quality and the edible biofilm products' antimicrobial ability. Classification is finding patterns or functions that describe and separate data classes from one another (Setio *et al.*, 2020). A decision tree model can divide an extensive data set into smaller record sets by applying decision rules (Setio *et al.*, 2020). The tree structure with node mode describes each attribute, each branch will represent the attribute test results, and each leaf will describe a class or label (Utari and Wibowo, 2020). The attribute that has the most influence appears at the top of the tree as the root node. The overall structure andq logic of the decision tree used in this research are visualized in Figure 2, which illustrates how the dataset is broken down through successive binary splits. The model provides a visual guide for classification based on attribute values.

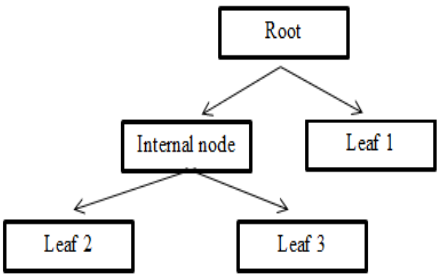

Figure 2. Decision Tree Model (Djatna, 2019)

To make the tree interpretable and usable for decision-making, it is converted into a set of if-then rules, which are detailed in Figure 3. These rules determine the path from the root to the leaf based on the input data, thus producing a classification outcome. We explore several metrics thatare essential when evaluating decision tree. The entropy of a dataset, calculated using Equation 1, measures the level of disorder or impurity. A higher entropy indicates greater heterogeneity in the dataset, requiring more splits to achieve homogeneity (Setio *et al.*, 2020).

$$\text{Entropy} = -\sum_{i=1}^{k} P_i \text{ x } \log_2 P_i \qquad \text{[Eq :1]}$$

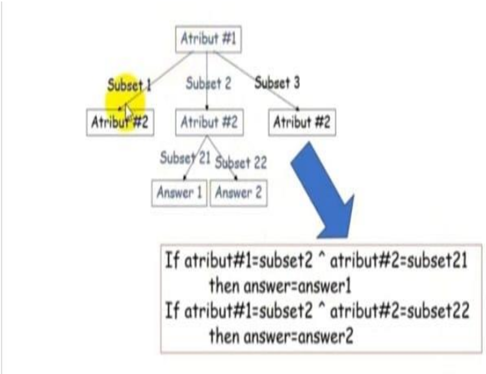

Figure 3. Decision tree rules (Djatna, 2019)

Next, the information gain, defined in Equation 2, helps determine which attribute offers the highest value in splitting the data effectively. The attribute with the highest gain becomes a candidate for a node.

$$\text{Gain} = \text{Entropy (S)} - \sum_{i=1}^{k} \frac{|S_i|}{|S|} \text{ x Entropy } (S_i) \qquad \text{[Eq :2]}$$

The gain value is used to determine which variable is the node of a decision tree. A variable with the highest gain will be used as a node in the decision tree. Calculate the split info value with the formula.

$$\text{Split Info } (S, A) = -\sum_{j=1}^{k} \frac{Sj}{S} \text{ x } \log_2 \frac{Sj}{S} \qquad \text{[Eq :3]}$$

Finally, the gain ratio is computed with Equation 4, which divides the information gain by the split info. The attribute with the highest gain ratio is selected as the root node, ensuring a balance between gain and data partitioning.

$$Gain\ R(S, A) = \frac{\text{Gain(S,A)}}{\text{Split (S,A)}} \qquad \text{[Eq :4]}$$

The decision tree is recursively built by selecting the best attribute (with the highest gain ratio) at each level, forming a hierarchical model until all branches lead to uniform class labels.

Formulation System Using Linear Regression OLS

Regression analysis is a statistical method used to establish relationships between variables and has broad applications across various scientific fields (Mahaboob *et al.*, 2018). Linear regression is a statistical technique used to analyze the linear influence between two or more variables (Djatna, 2019). In this context, linear regression can be applied to estimate the relationship between multiple independent variables (*x*) and their effect on a dependent variable (*y*).

The independent variable must exhibit a linear relationship with the dependent variable. The model must be linear because if the resulting model is non-linear, it fails to explain the systematic relationship pattern between the dependent and independent variables (Amirulloh and Taufiqurrochman, 2017).

The assessment of hedging effectiveness relies on the adjusted R^2 obtained from the regression model, with the slope coefficient serving as the optimal hedging ratio (Amirulloh and Taufiqurrochman, 2017). In OLS regression, nonlinearity introduces bias in the interpretation of the least squares estimator.

The Ordinary Least Squares (OLS) method applies the regression formula shown in Equation 5, which models the relationship between the variables:

$$Y_1 = ß_0 + ß_1X_1,\ i = 1, 2, n,... \qquad \text{[Eq :5]}$$

Where, $ß_0$ is intercepted, $ß_1$ is Slope, and the average regression coefficient of Y changes if X increases by 1 unit. X_1 is the independent variable, and Y_1 is the dependent variable.

The model's goodness-of-fit is evaluated using adjusted R^2, which indicates how well the model explains the variation in the dependent variable. A higher R^2 suggests a better model performance. This regression model is particularly useful in predicting continuous outputs, such as production yield or moisture content, in this edible biofilm production study.

RESULTS AND DISCUSSION

Analysis System and Modeling

The Digital Business Ecosystem (DBE) based antimicrobial edible biofilm production system integrates various elements through inputs in the form of appropriate raw material formulations. These inputs are applied through stages that include goal setting, scope determination, and system modeling. The interpretation of these processes serves as the foundation for formulating scenarios and improvements to optimize output, ensuring the production of edible biofilms that meet quality standards and criteria.

The analysis and design of the edible biofilm production system involve four key stakeholders: Research and Development (RnD), Quality Control (QC), Developer, and Production Staff. The system primarily focuses on the design of the edible biofilm production process, as illustrated in Figure 4.

This structured approach ensures that all relevant aspects of production, from raw materials to final output, are comprehensively considered. Involving multiple stakeholders early in the process fosters collaboration and helps identify potential challenges at different stages, increasing the chances of producing a high-quality product efficiently.

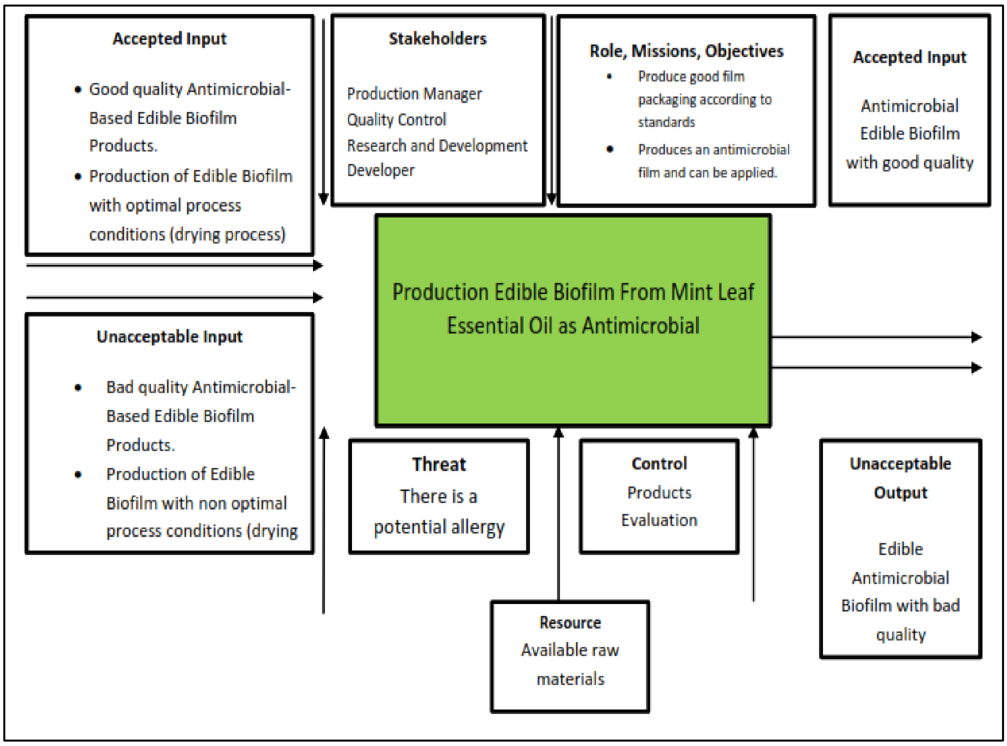

Figure 4. Analytical system entity of edible biofilm production

Use cases define the roles and relationships between actors and various business processes within an ecosystem. In this system, the use case consists of four key actors: Research and Development (RnD), Quality Control (QC), Production Manager, and Developer. Each actor performs specific roles and interacts with others throughout different process stages to achieve the intended goal.

The system includes eight business processes, which are detailed in Figure 5. Within the DBE framework, actor interactions occur digitally, enabling a faster, more efficient, and better-monitored process. It facilitates interaction among stakeholders, enabling actors within the ecosystem to communicate and exchange information through digital infrastructure (Amirulloh & Taufiqurrochman, 2017). The exchanged information includes production data, edible biofilm with good quality based on physical and mechanical characteristics and antimicrobial inhibition zone. Similar to the research conducted by Azmi *et al.* (2021), this DBE system was developed as an enhancement of system design based on life cycle assessment of broiler chicken. The exchanged information includes production data, waste and emissions, environmental impact analysis results, and recommendations for improvement

This approach aligns with the research conducted by Elallaoui *et al.* (2018), where an ATM usage system involves nine actors, including administrator, visitor, newly registered user, trainer, ATM user, ATM operator, site editor, and developer. The advantage of utilizing a use case diagram lies in its ability to streamline the development process by reducing ambiguity in requirement specifications and generating automated design models.

This use case model ensures transparency and role clarity, enabling stakeholders to communicate requirements and status updates more efficiently. It also aligns with best practices from previous studies (Elallaoui *et al.*, 2018), reinforcing its reliability in similar systems.

By defining clear roles and interactions, the system reduces ambiguity in task ownership, which is often a source of errors in production. Digital interaction streamlines communication, making coordination easier and enabling quick response to any issues that arise during production. Furthermore, the creation of UML use case diagrams enhances system comprehension and helps designers interpret user stories consistently, ensuring alignment within the development team throughout the design process.

The BPMN is a business process flow presented in graphical notation. Modelling with BPMN on the edible biofilm production system illustrates collaboration between RnD, Quality Control, Production Manager, and developer stakeholders in a precise sequence and process flow shown in Figure 6.

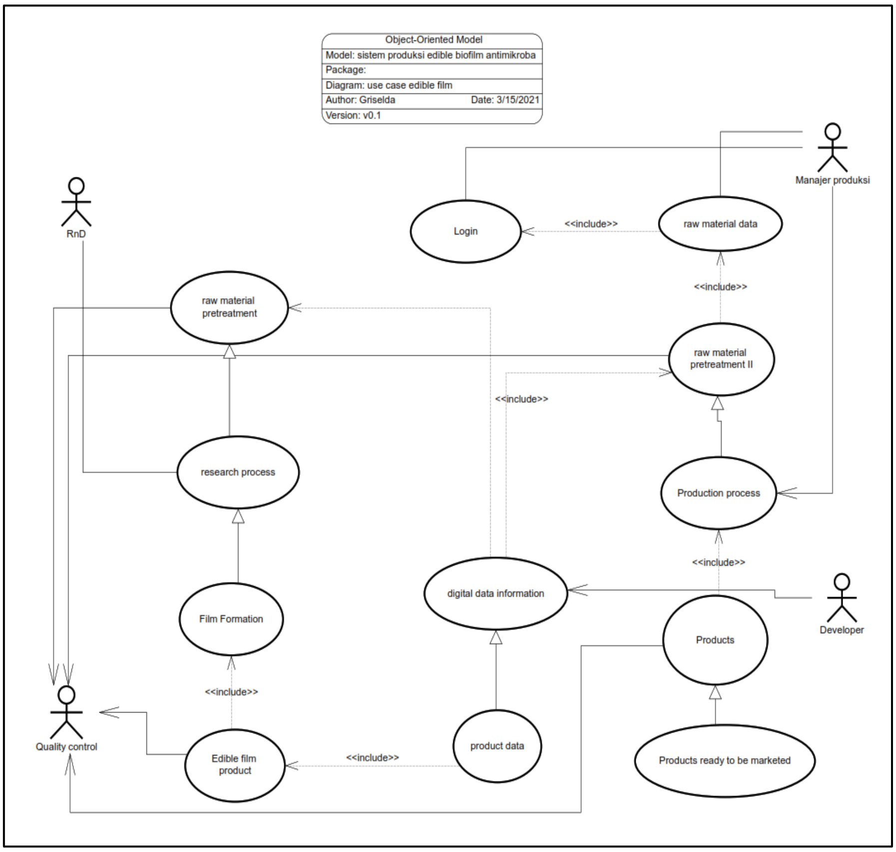

Figure 5. Use case diagram of edible biofilm production

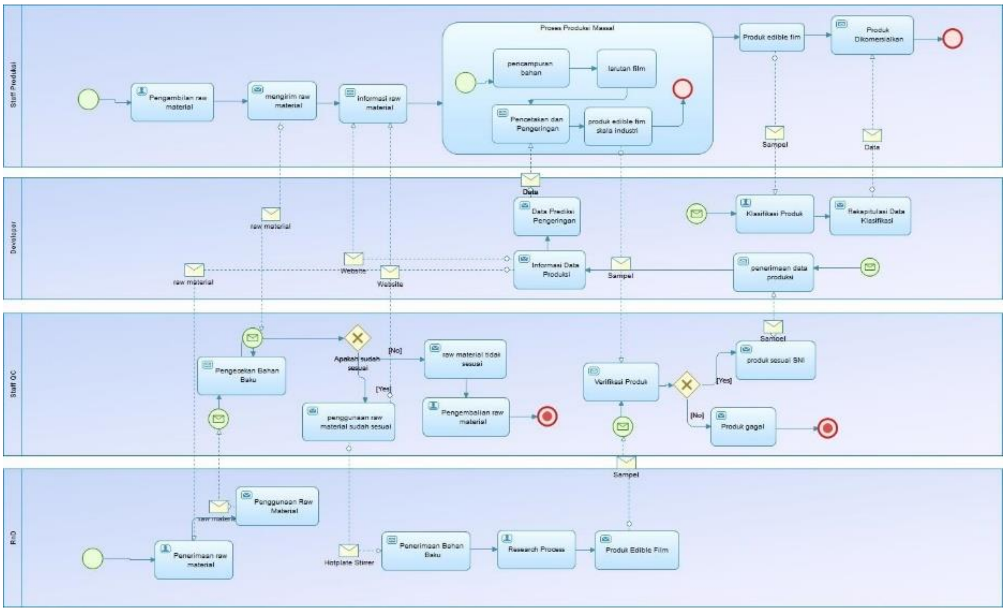

Figure 6. BPMN modeling of edible biofilm production

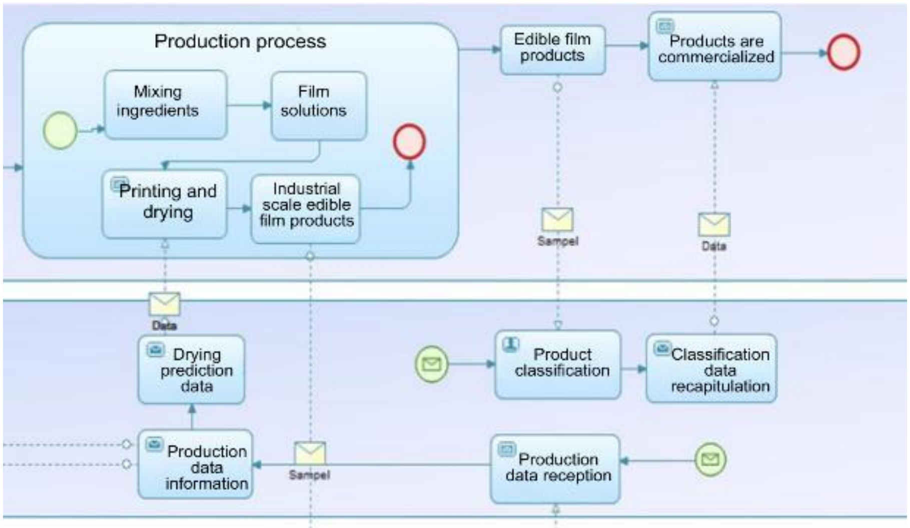

Figure 7. Process production of edible biofilm

Figure 6 shows the BPMN of the system created and verified, and no errors were found in the model. The BPMN model above illustrated the flow of an activity as a whole for the edible biofilm production process, starting from taking raw materials to checking the quality of raw materials, if the raw materials have been verified, experiments are carried out on a laboratory scale. The sample is then checked for quality by Quality Control, if the product produced is good and meets the standards, the production data is sent to the developer as information for the industrial-scale production process. Then narrowed down to the primary production process shown in Figure 7, after the production staff obtains data on raw materials, processes, and optimal process conditions from the developer, the industrial scale production process is carried out, and then the product is commercialized. Similar research was also conducted by Castro and Texeira (2020), they used BPMN to detect the number of activities that can predict waste for the company, both in terms of time consumption, space, and work in process (WIP), which reflects an increase in internal costs. The same research was conducted by Jaswadi *et al* (2021), they used BPMN to analyze the debt payment business process using BPMN as a research instrument and planning standard operating procedures based on business process diagrams as output from BPMN. The results of this study include the design of Standard Operating Procedures (SOP) for the debt payment business process at PO Dolopo Grosir. Meanwhile, in this study, the implementation of BPMN is used to estimate production at 500 units per day. The products are then classified to assess their quality and antimicrobial properties using decision tree machine learning, while OLS linear regression is applied to determine optimal drying conditions based on predictor variables.

All classification and prediction processes are conducted by the *developer* and subsequently communicated to the *production staff*. The BPMN-based process flow in this study integrates machine learning solutions to enhance production efficiency and decision-making. The visual representation of the process allows stakeholders to understand the flow and timing of activities. This transparency helps in identifying potential inefficiencies or bottlenecks and provides a framework for continuous improvement. Validation of the model confirms its practical feasibility. The model was validated with no errors, showing that the proposed workflow is logically structured and executable. The BPMN modeling not only facilitates visualization but also allows for early detection of inefficiencies or bottlenecks in the process (Jaswadi *et al.,* 2021). Additionally, machine learning integration via decision trees and regression models is visualized in this process to predict output and support decision-making.

Decision Tree

The decision tree is a flowchart-based model structured like a tree, where each inner node represents an attribute test, branches indicate test results, and leaf nodes represent class distributions (Amirulloh and Taufiqurrochman, 2017). This model is used to determine the quality of edible biofilms based on their physical and mechanical characteristics, including elongation, tensile strength (TS), and moisture content. The resulting decision tree model achieved an accuracy of 80.5%. This high accuracy indicates the model's reliability in predicting product quality, enabling rapid quality control decisions. Using measurable physical properties aligns with industry needs for standardized quality assessment, reducing subjective evaluation. The root node of the model is elongation, suggesting this attribute has the most significant influence on edible biofilm quality. The prediction and accuracy results of the decision tree model are presented in Table 1, while the classification rules for each category are summarized in Table 2.

Table 2 describes the classification of edible biofilm quality based on elongation and water content. An elongation value ≤ 9 and water content ≤ 9 indicate that the biofilm falls into the poor quality category. If elongation > 9 and tensile strength (TS) > 24, the biofilm is classified as good quality. Meanwhile, if elongation > 9 and TS is between 10 and ≤ 24, the biofilm is categorized as low quality. Tensile strength (TS) is the ability to receive the maximum load or tensile force of the film before breaking. Based on the requirements of packaging materials, edible film must have a level of resistance to cracking, abrasion resistance and flexible properties (Amirulloh and Taufiqurrochman, 2017).

The decision tree model in this study produced classification rules for edible biofilm quality based on a combination of three main parameters: elongation, moisture content, and tensile strength (TS). These three parameters play an important role in determining the mechanical characteristics and performance of edible biofilms, especially when intended as environmentally friendly active packaging materials.

Table 1. Prediction and accuracy model

	Actual		
Prediction	**Poor**	**Good**	**Bad**
Poor	50	0	1
Good	19	145	3
Bad	33	22	127
Accuracy	80.5%		

Table 2. Rules and class category

Rules	**Categories**
IF Elongation ≤ 9 and Water Content ≤ 9	Bad
IF Elongation >9 and TS ≤ 24 and also > 10	Poor
IF Elongation >9 and TS > 24	Good

Poor Quality Category

If the elongation value is ≤ 9 and the moisture content is ≤ 9, then the edible biofilm is classified as poor quality. A low elongation value indicates that the film is not flexible and is prone to breaking or tearing during use. Additionally, too low moisture content can make the film structure too stiff and brittle. The combination of these two parameters results in a biofilm that is physically inadequate for functional packaging material.

Good Quality Category

If elongation is > 9 and tensile strength (TS) is > 24, then the edible biofilm is categorized as good quality. High elongation indicates that the film is sufficiently elastic and flexible, while high TS indicates the film's ability to withstand a large tensile load before breaking. This combination describes a robust biofilm that meets active packaging standards by balancing flexibility and strength.

Low to Medium Quality Category

If elongation is > 9 and TS is between 10 and 24, then the biofilm is classified as low to medium quality. The film still has good flexibility but the tensile strength is not high enough to meet certain packaging standards. TS in the medium range indicates that the film is not optimal, though it is not as poor as the first category.

High moisture content in edible biofilms can cause excessive softness, increase the risk of microbial growth, and reduce mechanical stability. Conversely, too low moisture content can make the film brittle and prone to cracking. Therefore, optimal moisture content is essential to ensure a balance between flexibility and mechanical strength of the edible biofilm (Sulaiman *et al.*, 2023). This finding supports the classification model where moisture content ≤ 9 combined with low elongation correlates with poor biofilm quality.

Tensile strength measures the film's ability to withstand tensile force before breaking, while elongation measures how much the film can stretch before breaking. Both parameters are critical in determining the mechanical performance of edible biofilms. Therefore, balancing tensile strength and elongation is crucial to produce edible biofilms with optimal quality. The classification results indicate that high elongation alone is insufficient if tensile strength is inadequate, so both parameters must be considered simultaneously in formulation.

With this model, decision-making in the edible biofilm production process becomes easier, as products can be directly categorized based on physical test data. Furthermore, the results indicate that a combination of high elongation and high tensile strength is a key indicator of high-quality products, while moisture content must be controlled to avoid being too low or too high, as both extremes can negatively affect the mechanical characteristics of the film.

The decision tree model is also used to classify the antimicrobial effectiveness of the edible biofilm, determining whether it has strong, very strong, medium, or weak microbial inhibitory properties. The root node of the model is elongation, confirming that this attribute has the most significant impact on edible biofilm quality. The result of decision tree model achieved an accuracy of 95.74%, as presented in Table 3.

Table 3. Prediction and accuracy model

	Actual			
Prediction	**Strong**	**Weak**	**Very Strong**	**Medium**
Strong	112	0	8	1
Weak	0	100	0	0
Very Strong	0	1	89	0
Medium	6	0	0	81
Accuracy	95.74%			

Table 3 explains about the resulting model can present greater accuracy in the inhibition test compared to the quality of the film quality test. In the antimicrobial inhibition test, it was obtained at 95.74%. This shows a very high level of accuracy. Similar results were also produced in the research of (Amirulloh and Taufiqurrochman, 2017).

which produced a very high level of accuracy from the results of data classification testing using decision trees, with an accuracy of 99%, which has been carried out to detect patients affected by Covid-19. The rules of each class are concluded as follows in Table 4.

Table 4. Rules and class category

Rules	**Categories**
IF Diameter <5	Weak
IF diameter >5 and Atsiri Concentration 43	Very Strong
IF diameter >5 and ≤ 20	Medium
IF Diameter ≥ 20 and ≤ 43	Strong

If the antimicrobial inhibition zone diameter is < 5, the microbial inhibition ability is classified as weak. If the inhibition zone diameter is > 5 and the concentration of essential oil is > 43, the microbial inhibition ability is classified as very strong. If the inhibition zone diameter is > 5 and ≤ 20, the microbial inhibition ability is classified as medium. If the inhibition zone diameter is ≥ 20 and ≤ 43, the microbial inhibition ability is classified as strong.

Based on the results of the Decision Tree model, the antimicrobial ability of edible biofilm was classified into four categories: weak, medium, strong, and very strong by considering both the diameter of the inhibition zone and the concentration of essential oils. This classification closely aligns with the laboratory-based classification by Nuryanti *et al.* (2021), which categorizes antibacterial activity as weak (5 mm), medium (5–10 mm), strong (10–20 mm), and very strong (≥20 mm) based solely on inhibition zone diameter. However, the Decision Tree model adds value by integrating essential oil concentration, especially for distinguishing the "very strong" category, which requires a diameter >5 mm and essential oil concentration >43. This combined approach provides a more comprehensive understanding of antimicrobial performance. These findings suggest that Decision Tree predictions can serve as a reference or preliminary benchmark for real laboratory testing. The model acts as a decision-support tool to screen promising edible biofilm products, reduce the cost and time of experimentation, and enhance the efficiency and consistency of quality control in active food packaging production. Nevertheless, predictions should still be validated with direct laboratory tests to ensure their reliability and applicability in real world conditions.

Linear Regression

The dataset is divided into training data and test data, followed by the development of a machine learning model. In this study, the objective is to determine the optimal drying conditions for edible biofilms, with water content as the target variable. A higher water content indicates poor drying conditions. The water content variable is predicted using four predictor variables: water vapor transmission rate, humidity, temperature, and time. The resulting linear regression model is presented in Figure 8.

```
Call:
lm(formula = kadar.air.... ~ ., data = train)

Residuals:
    Min      1Q  Median      3Q     Max
-28.009  -4.741  -0.546   2.777  40.873

Coefficients:
                                  Estimate Std. Error t value Pr(>|t|)
(Intercept)                       25.61371    6.26232   4.090 5.29e-05 ***
Waktu.Pengeringan..jam.           -0.12527    0.12300  -1.018    0.309
suhu..C.                          -0.27762    0.04561  -6.086 2.89e-09 ***
Kelembaban.....                   -0.05823    0.05195  -1.121    0.263
Laju.Transmisi.Uap.Air..g.m2.jam.  1.30395    0.15516   8.404 9.43e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 8.362 on 370 degrees of freedom
Multiple R-squared:  0.6453,    Adjusted R-squared:  0.6414
F-statistic: 168.3 on 4 and 370 DF,  p-value: < 2.2e-16
```

Figure 8. Linear regression of drying process

These results indicate that call is a formula used to create a model. Residual is the error distribution of the prediction results. The intercept of drying conditions (moisture content) is 25.613-71 when all predictors are 0. The drying time increases by one will contribute negatively by -0.12527 to the drying conditions, and temperature and humidity will contribute negatively.

From, $Y_1 = ß_0 + ß_1X_1$, i= 1,2, n...... (Amirulloh & Taufiqurrochman, 2017).

So, the result based on that formula is

Drying conditions (moisture content) = 25.61371 – 0.12527 time – 0.27762 temperature – 0.05823 humidity + 1.30295 transmission rate.

The significance code of each independent variable shows that the p-value of temperature and water vapour transmission rate has a significant effect (p-value < 0) on drying conditions. In this case, more than one predictor for multiple R-squared is used, but it is ignored, and adjusted R-squared can be used as a reference. Adjusted R-squared is an evaluation model for multiple linear regression; the results show 0.6414, which means that the drying condition can be explained by 64% of the predictors included in the model. This indicates that the chosen predictors explain a significant portion of drying variability, providing actionable insights for optimizing drying processes. The model's statistical significance ensures that recommendations based on it are reliable for improving production efficiency and final product quality.

A linearity check is carried out to determine the linearity between the x and y variables. P value < 2.2e-16 indicates that H0 is rejected because the model is proven linear. Checking the correlation between variables can be done with the if () function of the drying conditions so that it is known which variables cannot be tolerated as predictors. When the VIF value > 10, then a variable must be eliminated. In this case, all variables show a VIF value < 10, so there is no need to eliminate variables.

Verification and Validation

Business Process Model and Notation (BPMN) and Use Case The production of edible biofilm has been running, and the results show no errors. A warning means that the model has been verified. The results of optimization with machine learning, Decision Tree and OLS Linear Regression can provide the best solution because they have been verified and validated. The optimization results with both machine learning show no wrong data encoding. The results show that the decision tree can classify edible biofilm quality, and the linear regression can predict the optimum condition of the drying process in edible biofilm production.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This study aimed to classify edible biofilm products to determine their quality and predict proper drying conditions. The results showed that the Decision Tree classification model successfully categorized edible biofilm quality into three levels (good, poor, and bad) based on elongation, tensile strength, and moisture content, with an accuracy of 80.5%. Additionally, antimicrobial ability was classified into four inhibitory levels (very strong, strong, medium, and weak) with a high accuracy of 95%. These findings indicate that the model is reliable for early prediction of product quality, which is crucial for maintaining food safety and shelf life. Moreover, the Ordinary Least Squares (OLS) linear regression model predicted drying outcomes with 64% explanatory power and statistically significant results (p-value < 0.05), suggesting a strong linear relationship between drying parameters (such as temperature and time) and final moisture content. Overall, the integration of system modeling (UML and BPMN) with machine learning techniques in this study provides an effective approach for supporting decision-making in edible biofilm production. This method enhances efficiency, ensures consistent product quality, and contributes to the development of smarter, more sustainable active packaging solutions in the food industry.

Recommendations

Based on the results of this study, it is recommended that the application of edible biofilm on an industrial scale be realized immediately, considering that various machine-learning methods have been widely recommended to help design active packaging systems.

REFERENCES

Ashrafudoulla MD, Mevo SIU, Song, Nahar S, Toushik SH, Park, SH, Ha SD. 2023. Antibiofilm mechanism of peppermint essential oil to avert biofilm developed by foodborne and food spoilage pathogens on food contact surfaces. *Journal Food Science.* 88(9): 3935-3955.

Amirulloh I and Taufiqurrochman T. 2017. Komparasi model klasifikasi algoritma keterlambatan siswa masuk sekolah. *Prosiding Seminar Nasional Teknologi. Seminar Nasional Sains dan Teknologi;* Jakarta, 1-2 November 2017. Jakarta: Fakultas Teknik Universitas Muhammadiyah Jakarta. hlm 1-4.

Aksoy C. 2023. Digital business ecosystems: An environment of collaboration, innovation, and value creation in the digital age. *Journal of Business and Trade*. 4(2) :156-180.

Azmi S, Djatna T, Suprihatin, Indrasti NS. 2021. Analysis and design of life cycle assessment system of chicken meat based on digital business ecosystem. *Jurnal Teknologi Industri Pertanian*. 31(2) :164-175.

Castro S and Teixeira L. 2020. BPMN and lean contributions for the ISO 9001 implementation: a case study within the plastics industry. *Proceedings of the 5th NA International Conference on Industrial Engineering and Operations Management Detroit*; Michigan 10 - 14 August 2020. Michigan: IEOM Society International. hlm 1228-1237.

Djatna T. 2019. Analisis dan Desain Sistem Produksi Agroindustri dengan Pendekatan Digital Business Eco-system. Bogor: IPB Press

Elallaoui M, Nafil K, and Touahni R. 2018. Automatic transformation of user stories into UML use case diagrams using the NLP technique. *Procedia Computer Science*. 130(2018): 42-49.

Erasmus MC and Geyser JM. 2024. Comparative analysis of futures contract cross-hedging effectiveness for soybean: models and insight. *Agricultural Economics Research*. 63(4): 319-336

Fatmawati F and Munajat J. 2018. Implementasi model waterfall pada sistem informasi persediaan barang berbasis web (studi kasus: PT. Pamindo Tiga T). *Jurnal Media Informatika. 8(1):1-9.*

Gadhi A, Gondu RM, Bandaru CM, Reddy KC, Abiona O. 2023. Applying UML and machine learning to enhance system analysis and design. *International Journal Communications, Network and System Sciences*. 16(1): 67-76

Gordon SL, Michael JA, and Berry. 2013. *Data Mining Techniques. Third Edition For Marketing, Sales, and Customer Relationship Management*. USA: Wiley Publishing Inc

Han J, Kamber, and Pei J. 2012. *Data mining: Data mining concepts and techniques*.USA : Elsevier

Irkin R and Esmer OK. 2015. Novel food packaging systems with natural antimicrobial agents. *Journal Food Science Technology*. 52(10): 6095–6111.

Juswadi, Sulthan N, and Sulistiono S. 2021. Designing debt payment standard operating procedures in the smes retail industry using Business Process Modeling and Notation (BPMN): A case study of a retailer in East Java, Indonesia. *Dinasti International Journal of Economics, Finance and Accounting*. 2(4): 378-386.

Kang J, Jin W, Wang J, Sun Y, Wu X, & Liu L. 2019. Antibacterial and anti-biofilm activities of peppermint essential oil against Staphylococcus aureus. *LWT 101*. 1(1): 639–645. https://doi.org/https://doi.org/10.1016/j.lwt.2018.11.093

Karimian Z, Tabatabaee A, and Sharifan A. 2019. Physico-mechanical and antimicrobial properties of isolated soy protein film incorporated with peppermint essential oil on raw hamburger. *Journal of Agricultural Science and Technology.* 5(1): 1-8.

Kautz O, Rumpe B, and Wachtmeister L. 2022. Semantic differencing of use case diagrams. *Journal of Object Technology*. 21(3): 1-15.

Mahaboob B, Venkateswarlu B, Narayana C, Ravi sankar J, Balasiddamuni P. 2018. A treatise on ordinary least squares estimation of parameters of linear model. *International Journal of Engineering and Technology*. 7(4): 518-522.

Nasiri M, Sani AM, Hakimzadeh V, Shahidi M. 2019. Antimicrobial effects of edible nano-composite based on bean pod shell gum, nano-TiO_2, and *Mentha Pulegium* essential oil. *Journal of Applied Biology and Biotechnology*.7(6):75-78.

Nisak SK and Nugraha J. 2018. Penerapan Klasifikasi Decision Tree dan Model Log Linear dalam Penanganan Kecelakaan Kerja. *Prosiding Seminar Nasional Matematika 1*; Semarang, 1

Februari 2018. Semarang:Matematika Universitas Negeri Semarang. hlm 445-455.

Nurhasanah N and Mudrikah II. 2025. Designing An Institutional Model For The Sunflower Agro-Industry Supply Chain. *Jurnal Teknologi Industri Pertanian,* 35(1): 8-22.

Nuryanti S, Naid T, and Hardiyanti V. 2021. Identification and antibacterial activity test of endophyte fungi mahoni bark (*Swieenia Mahagoni* L.) IFKBM04. *Journal Microbiology Science*. *1*(1): 9–15. http://jurnal.farmasi.umi.ac.id/index.php/microbiologyscience

Ravi TRS and Malathi P. 2022. Design and implementation of sales prediction model using decision tree regressor over linear regression towards increase in accuracy of prediction. *Advances in Parallel Computing*. 41(1): 522–529. https://doi.org/10.3233/APC220074

Olifia J. 2024. Improving port performance and modeling its impact using BPM and BPMN simulations: A case study of Batu Ampar Port. *Journal of Applied Business Administration*.8(2): 353-364

Parker GG, Van Alstyne MW, and Choudary SP. 2020. Platform Revolution: How Networked Markets Are Transforming the Economy. USA: Norton & Company

Setio PBN, Saputro DRS, and Winarno B. 2020. Klasifikasi dengan pohon keputusan berbasis algoritme C4. 5. *Prosiding Seminar Nasional Matematika 3*; Semarang, 28 Februari 2020. Semarang:Matematika Universitas Negeri Semarang. hlm 64-71. https://doi.org/10.24961/j.tek.ind.pert.2019.29.3.278

Subroto E, Indiarto R, Pangawikan AD, Prakoso FSH. 2021. Production and characteristics of composite edible biofilms based on polysaccharides and proteins. *International Journal of Emerging Trends in Engineering Research*. 9(2): 42-48.

Sulaiman I, Radiansyah, and Sihaloho NJ. 2023. Utilisation of clove oil in taro edible film as an antimicrobial agent. *Jurnal Teknologi Industri Pertanian*. 33(1):50-57.

Suwarda R, Irawadi TT, Suryadarma P, Yuliasih I. 2019. Stability of sago (*Metroxylon Sagu* rottb.) starch acetate edible film during storage under various temperatures. *Jurnal Teknologi Industri Pertanian.* 29(3): 278-289.

Utari DR and Wibowo A. 2020. Pemodelan Prediksi Status Keberlanjutan Polis Asuransi Kendaraan dengan Teknik Pemilihan Mayoritas Menggunakan Algoritma-Algoritma Klasifikasi Data Mining. *Seminar Nasional Teknoka*; Jakarta, 28 November 2020. Jakarta:Fakultas Teknik UHAMKA Jakarta. hlm 19-24

Yunitarini R and Hastarita F. 2016. Pemodelan proses bisnis akademik teknik informatika Universitas Trunojoyo dengan Business Process Modelling Notation (BPMN). *Simantec Journal*. 5(2):93–100.