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Halal Ingredient Detection in Packaged Food Products Using Multi-Layer Perceptron (MLP)

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Abstract

The halal status of ingredients in packaged food products is a significant concern for Muslim consumers, yet variations in label formats and technical terminology often hinder manual verification. This study introduces Halal Ingredient Detection in Packaged Food Products Using a Multi-Layer Perceptron (MLP). A dataset of 55,149 ingredient entries from OpenFoodFacts was automatically labeled using internationally recognized lists of prohibited ingredients. Preprocessing included case folding, stopword removal, and TF-IDF text representation. Various MLP architectures were evaluated by considering macro F1-score, training time, and model generalization. The best-performing architecture was a simple MLP with 16–8 neurons, using the Adam optimizer and binary cross-entropy loss. Using an 80:20 training–testing data split, the proposed MLP model achieved an accuracy of 94%, with the confusion matrix indicating low misclassification rates and strong discrimination between halal and non-halal ingredients. These results demonstrate that a straightforward MLP architecture combined with TF-IDF is sufficient to capture relevant textual patterns, providing an efficient and reliable approach for automated halal ingredient classification.

***Keywords**: Halal Detection, Ingredients, Packaged Food, TF-IDF, Multilayer Perceptron*

1. Introduction

Food is a fundamental human necessity that provides energy and nutrients essential for growth and daily activities. Along with rapid technological advancements and changing lifestyles, packaged food products have become a primary choice for modern consumers due to their convenience, ease of storage, and diverse varieties that cater to consumer needs. The global packaged food market has experienced significant growth, driven by rising demand for convenience, longer shelf life, and a wide range of products aligned with modern lifestyles. According to IMARC Group, the global packaged food market, valued at USD 2,618.2 billion in 2024, is projected to grow at an annual rate of 6.68% to reach USD 4,709.0 billion by 2033, as illustrated in Figure 1. This rapid growth reflects the rising consumption of packaged foods worldwide, ranging from ready-to-eat meals to snacks and raw ingredients.

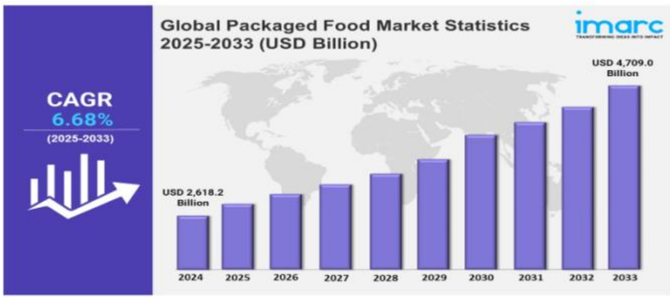

Fig. 1: Global Packaged Food Market Statistics
Source: https://www.imarcgroup.com/packaged-food-market-statistics

However, this rapid market growth presents increasingly complex challenges for Muslim consumers in ensuring the halal status of the products they consume, particularly given the vast number of packaged food products available. The dominance of major food corporations such as Nestlé, with a market capitalization of USD 316.71 billion [1], underscores the global prevalence of packaged foods, further complicating the identification and verification of product halal status. Besides protecting and preserving product quality, packaging also serves as an important means of conveying information to consumers. Packaging labels contain essential details such as ingredient lists, nutritional information, expiration dates, and halal certification, which play a critical role in purchasing decisions [2].

In Islam, halal food refers to foods or beverages that are permissible for Muslims to consume in accordance with Islamic law [3]. Halalness is not only a religious requirement but has also become an integral part of the lifestyle of Muslims worldwide [4]. Today, halal products have become a growing trend, particularly in the food and beverage sector [5]. Halal certification, indicated by a logo on the packaging, ensures compliance with Shariah standards and enhances consumer trust, including among non-Muslims, because it symbolizes cleanliness, quality, and safety [6].

In Indonesia, which has the world's largest Muslim population, totaling 231.06 million people (11.92% of the global Muslim population), the demand for halal products is exceptionally high, with domestic spending on halal products projected to reach USD 2.2 trillion [5]. However, only 9.6% of the 727,617 packaged food products circulating in Indonesia between 2011 and 2018 were halal-certified, indicating a significant gap in certification coverage [7]. This gap presents challenges for Muslim consumers, particularly when traveling to countries with Muslim-minority populations or purchasing imported products that lack clear halal certification.

Consumers have the right to obtain clear information about a product's ingredients, safety, nutritional content, and halal status before consumption [8]. Good label readability is essential for promoting transparency and building consumer trust [9]. However, unclear or confusing labels may create doubt and potentially lead consumers to unknowingly consume products that do not comply with Islamic dietary laws. Various technology-based efforts have been undertaken to address this issue. Previous studies have developed applications using barcode scanners [10] and Optical Character Recognition (OCR) technology [11][12] to scan product labels and match them with halal databases. Although effective at improving consumer confidence, most of these applications rely on direct matching and cannot automatically classify food ingredients. In reality, the variations in ingredient terminology, whether scientific names or foreign-language terms, often make it difficult for consumers to determine a product's halal status.

To address these challenges, various technology-based approaches have been explored. Previous studies have developed halal identification systems based on database matching and rule-based methods [10]. While these approaches can assist consumers, they generally rely on exact keyword matching and lack the capability to automatically classify ingredient compositions based on learned textual patterns. Consequently, such systems struggle to handle synonym variations, affixation, or alternative scientific naming conventions commonly found in ingredient lists.

To overcome these limitations, this study focuses on applying machine learning techniques, specifically the Multi-Layer Perceptron (MLP), to classify the halal status of packaged food products using ingredient text data. MLP is a feedforward neural network capable of learning complex and non-linear patterns through multiple hidden layers and activation functions such as ReLU or sigmoid, optimized using backpropagation [13][14]. Due to its strong pattern recognition capabilities, MLP has been widely applied to text classification tasks and has demonstrated competitive performance across various domains [15][16].

The identification of halal status in packaged food products is an important application of information technology, as it helps Muslim consumers make informed purchasing decisions. In this study, ingredient lists are processed through text preprocessing and represented using Term Frequency–Inverse Document Frequency (TF-IDF) features. These features are then classified using an MLP to distinguish halal from non-halal ingredients. Model performance is evaluated using standard classification metrics to assess accuracy and generalization, and architectural tuning is performed to improve classification results. Although prior studies have explored halal product identification, most rely on rule-based or exact-string-matching approaches and do not use feature-based machine learning models to learn semantic patterns in ingredient compositions. Furthermore, the application of MLP for halal–haram classification using textual ingredient features has not been extensively investigated. Therefore, this research addresses this gap by proposing an MLP-based classification approach using TF-IDF features to automatically infer the halal status of packaged food products based solely on ingredient text.

Based on these considerations, this study proposes a halal ingredient detection model using a multi-layer perceptron. Ingredient composition data are transformed into textual features and classified into halal or non-halal categories by the MLP model. This approach is expected to provide an efficient and reliable solution for automated halal ingredient classification, thereby helping Muslim consumers make informed purchasing decisions.

2. Literature

2.1. Related Works

Research on halal product identification has gained increasing attention due to the growing demand among Muslim consumers for accurate and accessible information regarding the halal status of packaged food products. Various technological approaches have been proposed, ranging from database-based identification systems to machine learning models for ingredient classification. Early studies primarily relied on database matching and rule-based systems to identify halal products. For example, barcode-based applications were developed to match product identifiers with lists of halal-certified products stored in centralized databases [10]. While these systems improved consumer confidence, they were limited to registered products and could not analyze ingredient compositions, making them ineffective for newly released or imported products not included in the database.

Several studies have explored machine learning approaches to improve classification accuracy in textual data. In [16], multiple algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), and MLP, were evaluated for text classification tasks. The results showed that MLP achieved competitive performance, demonstrating its ability to model non-linear relationships in textual features. Similarly, research by [17] compared MLP with traditional machine learning algorithms in chemical molecule classification using textual representations and reported that MLP achieved the highest accuracy of 92%. Despite these advancements, most halal identification systems still rely on exact keyword matching rather than learning discriminative textual features. Such approaches are vulnerable to variations in ingredient terminology, synonyms, chemical naming conventions, and stylistic differences in labeling. As a result, they lack robustness and generalization capability when applied to diverse ingredient compositions.

This study addresses these limitations by employing a Multi-Layer Perceptron classifier with TF-IDF-based textual features to perform halal–haram classification. By learning statistical patterns from ingredient text data, the proposed approach moves beyond rigid string matching and enables more adaptive and generalized classification across a wide range of packaged food products. The application of MLP for halal ingredient classification based on textual features remains relatively underexplored, highlighting the contribution of this research to the advancement of intelligent halal detection systems.

2.2. Deep Learning

Deep learning, as a branch of machine learning, offers more advanced and complex data processing capabilities. By leveraging multilayer artificial neural networks, deep learning can construct hierarchical representations of data, enabling the recognition of patterns that are difficult to identify using traditional methods [18]. The non-linear transformations applied at each layer make these models particularly effective in handling non-linear data, which is commonly found in text and image data.

Deep learning has been widely applied across domains such as computer vision, natural language processing, and speech recognition [19]. In the context of halal detection, the ability of deep learning models to recognize variations in fonts, sizes, and label designs is especially important. Packaged food labels are often designed creatively, which can pose challenges for classical methods. With better generalization capabilities, deep learning is expected to improve the accuracy of text extraction and food ingredient classification.

2.3. Multi-Layer Perceptron

The Multilayer Perceptron (MLP) is one of the most widely used artificial neural network architectures for classification tasks. This architecture consists of an input layer, several hidden layers, and an output layer, with weight updates performed through backpropagation [20]. Non-linear activation functions, such as ReLU and sigmoid, enable MLPs to handle data that are not linearly separable [21]. Several studies have demonstrated the advantages of MLP across various domains. [15] reported nearly 99% accuracy in complex handwritten character recognition using MLP. [16]found that MLP achieved high accuracy in invoice text classification, competing effectively with other algorithms such as SVM.

Recent research by [17]also showed that MLP outperformed Decision Tree and CatBoost models in text-based data classification. These empirical findings indicate that MLP is a suitable choice for classifying food ingredients, which often contain diverse and non-standardized terminology. Moreover, MLP offers flexibility in processing text input Ingredient composition data can be converted into numerical representations, such as TF-IDF or Bag of Words, and then processed by an MLP to classify food as halal or non-halal. Another advantage of MLP is its ability to improve performance through iterative training, allowing the model to adapt to new variations in ingredient terminology over time.

3. Methodology

3.1. Research Design

This study is designed as applied research with a quantitative approach, aiming to develop a practical solution to help Muslim consumers identify the halal status of packaged food products. The research workflow begins with a literature review to establish the theoretical foundation, followed by data collection from the OpenFood Facts and Kaggle datasets. The collected data then undergo a preprocessing stage to ensure data quality and readiness for analysis. Although the data are textual, all information is converted to numerical representations using vectorization techniques to enable systematic mathematical processing. The preprocessed dataset is then split into training and test sets. The training data are used to train a Multilayer Perceptron (MLP) model, while the testing data are employed to evaluate the model's performance. The final stage involves model evaluation to assess the system's ability to classify food ingredients as halal or non-halal, as illustrated in the research workflow presented in Figure 2.

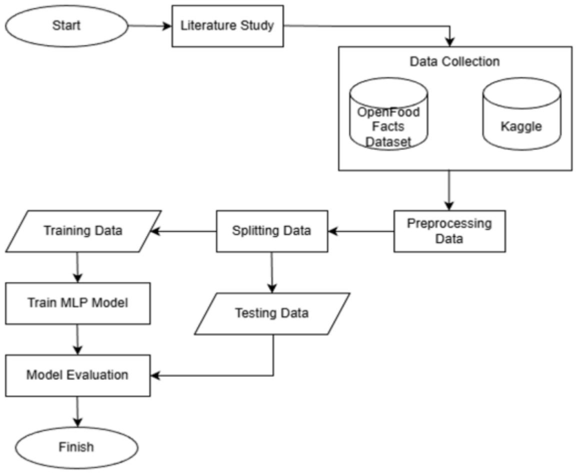

Fig. 2: Research Design

3.2. Dataset

The data used in this study were obtained from various credible open-source platforms providing information on food products and their halal status. The primary sources include OpenFoodFacts, Halal Advisory Service, halalrc.org, and halal.addi.its.ac.id. These databases were selected for their diverse ingredient composition information, accompanied by halal or non-halal status, which served as references for data labeling. The collected dataset consists of textual ingredient lists from packaged food products, subsequently processed into Comma-Separated Values (CSV) format to facilitate analysis and integration into machine learning models. Each entry includes the ingredient name, halal or non-halal category, and supporting metadata. The primary variable of interest is the list of ingredients, serving as input features, while the halal/non-halal label serves as the target output for detection. The total dataset comprises 55,149 food product entries with diverse ingredient compositions. Table 1 provides an overview of the dataset structure used in this study.

Table 1: Dataset

Ingridients
Dried Prunes, Water, Corn Syrup, Sugar, Pectin.
Salt, Yellow 5 Lake, Tricalcium Phosphate and Artificial Butter Flavor
Wheat Flour, Soybean Oil, Salt, Dehydrated Garlic, Sugar, Onion Powder, Garlic Powder, Yeast, Spices, Contains: Wheat.
Tomato Puree, Water, Tomato Paste, Brown Sugar, Apple Cider Vinegar, Fresh Onions, Salt, Ground Beef, Ground Pork, Green Bell Peppers, Mustard, Fresh Celery, Modified Food Starch, Imported Olive Oil, Chili Powder, Spices, Garlic.
Garlic, Water, Citric Acid, Sodium Benzoate.

4. Results

4.1. Data Preprocessing

Data preprocessing was conducted to ensure the dataset was ready for machine learning algorithms. Raw data from various sources often contain inconsistencies, duplicates, and non-standard terminology, making this step crucial for producing clean, standardized, and relevant data. The first step, data cleaning, involved removing incomplete, duplicate, or irrelevant entries. Term normalization was also performed to unify variations, such as standardizing "flavouring agent" to "flavoring agent" or harmonizing scientific nomenclature, ensuring consistent representation. Next, tokenization and stopword removal were applied, splitting ingredient lists into individual tokens and eliminating common words without specific meaning (e.g., "and," "with," "contains") to reduce noise while retaining relevant information.

Finally, the textual data were transformed into numerical representations using Term Frequency-Inverse Document Frequency (TF-IDF), which measures the importance of each word relative to the entire dataset. This representation converts ingredient compositions into numerical vectors suitable for Multilayer Perceptron (MLP) processing. These preprocessing steps produced a clean, structured dataset, enabling the model to learn meaningful patterns that determine halal and non-halal status rather than superficial textual patterns.

4.2. Modelling

The model developed in this study is a Multilayer Perceptron (MLP), a widely used artificial neural network architecture for classification tasks. MLP consists of an input layer, several hidden layers, and an output layer, with weights adjusted using the backpropagation learning algorithm [20]. Non-linear activation functions such as ReLU and sigmoid enable MLP to handle data that cannot be linearly separated. The MLP architecture is composed of multiple interconnected perceptron layers. Increasing the number of layers and neurons enhances the model's processing complexity, allowing it to learn more specific and optimal representations of the training data [21]. MLP employs supervised learning through the backpropagation algorithm to optimize network weights. Unlike linear perceptrons, MLPs use non-linear activation functions, enabling them to process data with complex decision boundaries. The classification process begins by multiplying the input vector by the corresponding weights, then applying activation functions at each layer. Information flows one-way from the input layer to the output layer through one or more hidden layers, classifying MLPs as feedforward neural networks [22]. The selection of MLP in this study is based on its advantages in recognizing nonlinear patterns and its ability to process textual data. Leveraging its feedforward structure and backpropagation algorithm, the MLP is expected to achieve high classification accuracy in determining whether an ingredient is halal or non-halal. The MLP architecture used in this Research consists of an input layer, multiple hidden layers, and an output layer. The input layer receives numerical representations of ingredient composition text generated using the TF-IDF method. These data are then passed into the hidden layers, each equipped with non-linear activation functions such as the Rectified Linear Unit (ReLU), enabling the network to learn complex patterns that cannot be linearly separated. The overall workflow of the model is illustrated in Figure 3, showing the operational flow of the Multilayer Perceptron (MLP) algorithm applied in this study.

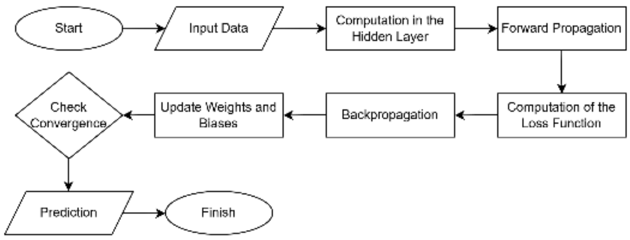

Fig. 3: Multi-Layer Perceptron Algorithm

The MLP architecture consists of an input layer, multiple hidden layers, and an output layer. Input data, represented numerically via TF-IDF, passes through hidden layers with ReLU activation to learn complex, non-linear patterns. The model is trained using backpropagation, with SGD or Adam optimization to improve convergence and accuracy. Training parameters, including epochs, batch size, and learning rate, are determined through preliminary experiments for optimal performance. Table 2 shows various combinations of neuron counts and hidden layers are tested to determine the most effective and efficient MLP architecture for this task.

Table 2: MLP Architecture Experiments

Number of Neurons Per Hidden Layer	Dropout	Dropout Rate
8	No	-
16,8	No	-
32,16,8	No	-
32,16,8	Yes	0.5
32,16,8	Yes	0.3

Each architecture was trained on the same dataset with consistent training parameters: the Adam optimizer with a learning rate of 0.001, a batch size of 32, and early stopping when validation loss did not improve for 5 consecutive epochs. Dropout was implemented in some architectures to mitigate overfitting by randomly deactivating a portion of neurons during training. The Multilayer Perceptron (MLP) model was trained using the preprocessed dataset. Several network architectures were tested to identify the best-performing model, based on F1-Macro score, training time, the best validation loss, and the number of epochs required for convergence. The results of these tests across different MLP configurations are presented in Table 3.

Table 3: Results of Testing Multiple MLP Architecture Configurations

Architecture	F1-Macro	Time (s)	Best Val Loss	Epochs
(8)	0.9391	126.72	0.1567	12
(16,8)	0.9468	120.36	0.1350	8
(32,16,8)	0.9443	155.88	0.1468	8
(32,16,8) + 0.5	0.9449	163.32	0.1500	8
(32,16,8) +0.3	0.9466	139.47	0.1447	7

The results indicate that the (16,8) architecture achieved the highest F1-Macro score of 0.9468, with a training time of 120.36 seconds and the lowest best validation loss of 0.1350, making it the best-performing configuration among those tested. The (32,16,8) architecture and its variants with dropout rates of 0.5 and 0.3 yielded slightly lower F1-Macro scores, ranging from 0.9443 to 0.9466, and longer training times than the (16,8) architecture. Although the (8) architecture required the shortest training time (126.72 seconds), it had the lowest F1-Macro score of 0.9391.

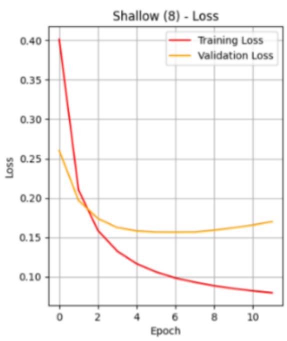

Fig. 4 (a): Shallow

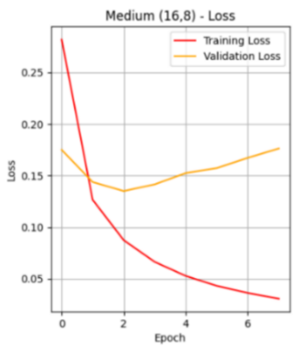

Fig. 4 (b): Medium

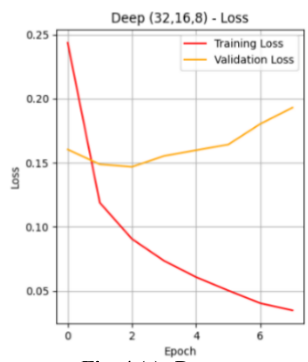

Fig. 4 (c): Deep

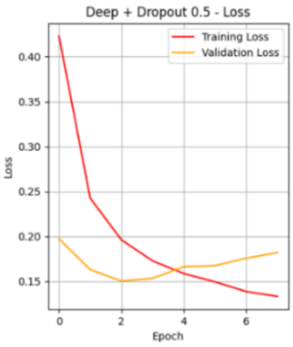

Fig. 4 (d): Deep+ Dropout 0.5

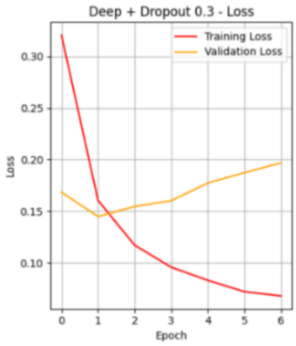

Fig. 4 (e): Deep+Dropout 0.3

Figure 4 presents loss graphs for various MLP architectures. The simple architecture (8) learns effectively without overfitting. The medium architecture (16,8) delivers the most stable performance despite minor signs of overfitting. The deep architecture (32, 16, 8) tends to overfit, but applying dropout (0.3 and 0.5) reduces overfitting and improves generalization. The effectiveness of the 16–8 architecture stems from sufficiently discriminative TF-IDF features, meaning the model does not require a large capacity that could lead to overfitting. Thus, the 16–8 architecture offers the best balance between accuracy, training time efficiency, and computational cost. This indicates that the dataset has clear patterns, so a moderate architecture is sufficient to achieve optimal results without unnecessarily increasing network complexity.

4.3. Model Evaluation

As explained in the model performance section, the MLP architecture with a 16–8 neuron configuration was selected as the best model because it offers the most balanced performance across accuracy, F1-score, and training time efficiency. To ensure the consistency of this model's performance, further evaluation was conducted using an 80:20 train-test split, with the classification report presented in Table 4. This report summarizes the precision, recall, F1-score, and accuracy metrics for both halal and haram classes, demonstrating the model’s effectiveness in classifying food ingredient data.

Table 4: Classification Report

	Precision	Recall	F1-Score
Halal	0.95	0.97	0.96
Haram	0.94	0.91	0.92
Accuracy			**0.95**
Macro Avg	0.94	0.94	0.94
Weighted Avg	0.95	0.95	0.95

The proposed model achieves an overall accuracy of 94%, indicating it performs well at classifying halal and non-halal food ingredients. This level of accuracy demonstrates that the model is reliable and effective for practical halal food identification tasks.

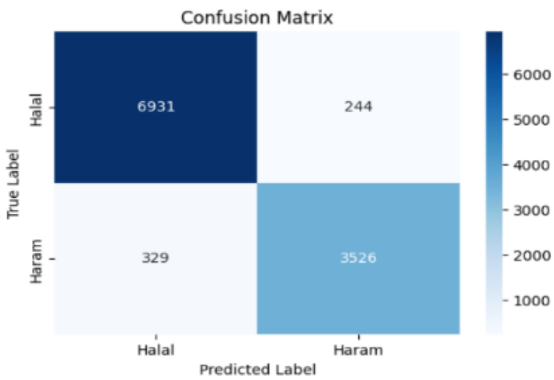

Figure 5: Confusion Matrix

Figure 5. Confusion matrix illustrating the performance of the classification model in distinguishing between halal and haram food ingredients. The model correctly classified 6,931 halal samples and 3,526 haram samples, while misclassifying 244 halal samples as haram and 329 haram samples as halal. The visualization highlights strong predictive accuracy for both classes, with a higher concentration of correctly classified instances along the diagonal.

The stable performance across all scenarios also confirms that the TF-IDF–based text representation method successfully extracted key terms that determine halal status, while the 16–8 MLP architecture effectively learned these patterns. Ingredient terms such as gelatin, alcohol, and emulsifier emerged as highly influential features, and the model recognized them even when the proportion of training data varied. These findings further indicate that a simple yet effective architecture is preferable to unnecessarily increasing network complexity.

Table 5: Comparison Between MLP and conventional baseline methods

Model	Accuracy
Logistic Regression	0.84
Naive Bayes	0.85
KNN	0.88
SVM	0.89
MLP (16–8)	**0.94**

Table 5 presents a comparison between the Multi-Layer Perceptron (MLP) algorithm and several simple baseline models used in this study. This comparison was conducted to ensure that the performance improvement achieved by the MLP is genuine and not merely a result of architectural variation without an objective benchmark. Therefore, the study also evaluates the performance of MLP against several simpler baseline models namely Logistic Regression, Naïve Bayes, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) as shown in Table 4.

The evaluation results indicate that the baseline models achieved accuracy scores ranging from 0.83 to 0.89, with Logistic Regression achieving the lowest (0.84) and SVM achieving the highest (0.89). In contrast, the MLP model with a 16–8 configuration achieved an accuracy of 0.94, improving by approximately ±5 percentage points over the best-performing baseline model (SVM). This performance gap demonstrates that the MLP's superiority is not merely due to switching to a different model, but rather its inherent ability to learn non-linear patterns within the TF-IDF representation patterns that linear or distance-based models are unable to capture effectively.

Thus, the application of MLP in this study serves not only as an alternative algorithmic approach but also provides a significant empirical advantage over conventional baseline models. Based on these findings, it can be concluded that the 16–8 MLP architecture is not only optimal but also reliable and consistent. Its performance stability across various data-splitting scenarios further reinforces its readiness for real-world implementation, where data conditions are often imperfect and highly variable.

5. Discussion

The results of this study demonstrate that integrating Multilayer Perceptron (MLP) provides a practical solution for detecting the halal status of packaged food products. The novelty of this research lies in the application of MLP combined with TF-IDF text representation for halal–haram classification, which has rarely been explored in previous halal detection studies. This approach enables the system to effectively analyze ingredient composition text and automatically determine halal status based on textual patterns. With consistent accuracy and F1-scores reaching 94% across various dataset splits, the model exhibits strong generalization capability. These findings are in line with studies by [15][16], which highlight the effectiveness of MLP in recognizing complex and diverse text patterns.

The MLP's performance of 94% also indicates a significant improvement over baseline models such as Logistic Regression (84%), Naïve Bayes (85%), KNN (88%), and SVM (89%), showing a difference of approximately ±5 percentage points compared to the best-performing baseline. This advantage is consistent with [22], who notes that MLPs' multiple layers and nonlinear activation functions enable them to separate data that are not linearly separable, unlike baseline models that are generally linear or assume specific data distributions. Furthermore, compared to previous studies, the 94% accuracy achieved in this Research represents an improvement; for instance, [16] and [17] reported MLP accuracies of 91.36% and 92%, respectively. This difference can be attributed to the data characteristics in this study, where TF-IDF-based text representation produces more discriminative features for halal and non-halal categories.

A key finding is that a simple architecture with a 16–8 neuron configuration yields more stable performance than a more complex architecture, such as 32–16–8 neurons. Two main reasons explain this phenomenon. First, the TF-IDF representation already provides highly discriminative features, as each word is quantified based on frequency and relevance within the corpus, reducing the need for a large network capacity to learn relevant patterns. Second, deeper architectures increase the risk of overfitting, particularly when the dataset features are already well-structured. This aligns with research of [17], which emphasizes that excessive complexity does not necessarily translate into improved text-processing performance.

Evaluation using the confusion matrix further showed that classification errors were relatively small, primarily occurring with technical or scientific terms that are rarely encountered, such as specific chemical derivatives that are difficult to categorize as halal or haram based solely on the composition text. Errors were classified into false positives, where neutral terms were misclassified as haram due to similarity with prohibited ingredients (e.g., "lecithin" vs. "gelatin"), and false negatives, where haram ingredients were missed because they were not included in the keyword list. This pattern indicates that the model still relies on vocabulary-based learning without deep semantic understanding. Future system development could integrate a richer halal food ontology or knowledge base to improve handling of synonyms, scientific terminology, and ambiguous ingredient contexts.

This study demonstrates that combining TF-IDF text representation with a Multilayer Perceptron (MLP) classifier is an effective approach for halal–haram food ingredient classification. The experimental results show consistently high accuracy and F1-scores of 94%, indicating strong generalization performance across different dataset splits. The findings also reveal that a simpler MLP architecture can achieve more stable results than deeper configurations when discriminative textual features are already well represented. These results contribute theoretically by reinforcing the effectiveness of MLP-based models for text classification in the halal food domain. However, this study is limited to modelling and dataset-based experiments; therefore, future research may extend this work by integrating OCR-based text extraction, expanding dataset diversity, and incorporating semantic knowledge to further improve classification performance.

6. Conclusion

This study concludes that the Multilayer Perceptron (MLP) model, particularly a simple architecture with 16–8 neurons, provides greater stability and efficiency than more complex architectures, achieving a consistent performance of 94% across various dataset splits. The proposed model outperforms conventional baseline methods by up to 5 percentage points, demonstrating its effectiveness for halal–haram food ingredient classification. Confusion matrix analysis indicates that classification errors are relatively minor and mainly occur with rare technical or scientific terms, suggesting that the model performs reliably on commonly encountered ingredient data. Overall, this research reinforces existing literature on the applicability of machine learning models, especially MLP, for text-based halal classification tasks.

Despite the strong performance of the proposed classification model, several limitations remain. The dataset used in this study does not fully represent global variations in packaged food products, and the classification relies solely on textual ingredient information without incorporating broader contextual or semantic knowledge. Therefore, future research may explore the use of advanced NLP models such as BERT or RoBERTa through fine-tuning to enhance contextual understanding, the collection of more diverse and multilingual datasets with expanded haram ingredient coverage, and the integration of external knowledge sources, such as halal ingredient databases or certification references, to improve classification robustness and generalizability.

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