

Recent Integrating Machine Learning and Malay-Arabic Lexical Mapping for Halal Food Classification

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Abstract—The rapid growth of e-commerce has changed the way people engage with businesses, notably in the food industry. For the Muslim community, guaranteeing Halal conformity in digital transactions is critical. This study provides a comprehensive framework for improving Halal E-Commerce systems that include machine learning, pattern libraries, and multilingual support, specifically in Malay and Arabic. The study examines the role of pattern libraries in designing user-friendly interfaces, as well as lexical mapping strategies for enhancing Malay-Arabic translation accuracy. Natural language processing (NLP) and machine learning are combined to create an application that classifies food items into two categories: Halal or Haram. With an accuracy of 85%, a Random Forest classifier is trained on labeled datasets. Preparing the text, extracting features using TF-IDF, and evaluating the results using precision, recall, and F1-score are all steps in the classification process. To increase classification accuracy, a rule-based approach is also applied to conditional logic and keyword matching. By adjusting the parameters, the model is further improved, leading to strong performance. By taking into account the cultural and linguistic requirements of the Muslim community, multilingual support enhances accessibility and user confidence. The suggested method increases translation accuracy by employing lexical mapping at the word, phrase, and context levels. The paper also assesses several machine learning models, demonstrating that Random Forest outperforms the other methods examined. The findings contribute to the growth of Halal E-Commerce by outlining a systematic strategy to ensure compliance and usability. The proposed system can serve as a platform for future research into AI-driven Halal certification and digital marketplace optimization, blockchain with an e-Commerce framework.

Keywords—Malay-Arabic lexical mapping; natural language processing; machine learning; halal food classification; halal food e-commerce

I. INTRODUCTION

The rise of e-commerce has altered consumer behavior and modified global food supply chains, providing unprecedented access to a wide range of items [1]. During this digital

transformation, the Muslim consumer group faces special hurdles, most notably assuring Halal compliance with food products. Halal, as a religious necessity, necessitates rigorous adherence to Islamic dietary requirements, and current Internet retail platforms typically fail to provide sufficient transparency and contextual information [2]. Product descriptions, certificates, and ingredients get increasingly complicated as they are written in multiple languages and cultural contexts. A fundamental issue in current Halal verification methods is their reliance on static certification markings, which may be out of date, regionally specific, or linguistically incomprehensible. Furthermore, the lack of real-time, automated, and linguistically inclusive verification methods severely impedes the development of culturally responsive digital food classification technologies [3]. Despite the growing emphasis on ethical consumption and religious inclusion, current platforms sometimes lack advanced computational techniques or multilingual semantic frameworks, both of which are required for effective Halal verification in cross-border e-commerce.

Simultaneously, modern usability requirements need systems that satisfy functional objectives while also providing a smooth and culturally adaptive user experience. According to user interface design and accessibility studies, pattern libraries are critical for creating consistent, intuitive interfaces that boost user confidence and interaction [4]. Multilingual support is equally vital, and Arabic remains the principal language of Islamic jurisprudence, whereas Malay is the predominant means of communication among Southeast Asian Muslim communities [5]. The purposeful use of various languages allows for semantic clarity and broad accessibility. Existing research has stressed Arabic's liturgical relevance as well as Malay's regional significance in the spread of Islamic knowledge [6]. However, there has been minimal research on developing lexical alignment between these languages for Halal food classification [7]. Given the linguistic discrepancies between ingredient labeling and certification forms, an intelligent system that bridges Arabic-Malay lexical mappings can drastically reduce

misinterpretation and improve classification accuracy. This gap in multilingual lexical integration within Halal certification systems is largely investigated in the literature.

Recent improvements in machine learning (ML) offer effective methods for automating difficult classification tasks. Machine learning algorithms can be trained to recognise non-Halal materials, assess multilingual product descriptions, and detect small linguistic cues suggesting Halal or Haram status [8][9]. However, their ability to classify Halal remains uncertain in the absence of culturally relevant linguistic information [10]. Thus, integrating machine learning with domain-specific Malay-Arabic lexical mapping improves context understanding, reduces false positives, and enables real-time, scalable Halal compliance solutions in food eCommerce platforms.

The paper describes an integrated system for automated Halal food classification in multilingual digital contexts based on machine learning and Malay-Arabic lexical mapping. The suggested technique bridges the research gap by incorporating cultural-linguistic information into data-driven models, thereby connecting technical capabilities to Muslim clients' religious and ethical requirements. This study adds to academic discourse and the development of inclusive, intelligent Halal eCommerce infrastructures by evaluating the existing state of the art, establishing a clear approach, and giving practical design solutions.

II. LITERATURE REVIEW

A. The Evolution of Halal e-Commerce

The rise of e-commerce has created new opportunities to connect specialist product categories with global audiences, particularly in faith-based marketplaces such as Halal food. Saleem et al. [1] argue that introducing Halal certification into digital platforms is more than simply a branding tool. It is critical for maintaining religious compliance and consumer trust. Nurillah [2] highlights the significance of cross-border transparency, traceability, and regulatory alignment in digital Halal ecosystems. Furthermore, Yener [3] claims that user-centric design, which incorporates culturally relevant factors such as dietary filters and religious certifications, may enhance trust and purchasing confidence among Muslim customers. These studies demonstrate a growing demand for digital solutions that not only permit compliance but also include Islamic values in the user experience (UX) design.

B. Role of Multilingual Support in e-Commerce

Language is a critical component of user interaction with digital services. Haque [5] argues that multilingual support improves accessibility greatly, particularly among linguistically heterogeneous user populations. For Halal systems, integrating Arabic (because of its religious significance) with Malay (in part due to its widespread adoption in Southeast Asia) assures not just language but also cultural resonance. According to Mabrurroh and Khoiriyah [6], adopting these languages fosters diversity and matches the user experience with the expectations of observant Muslim customers. This concept contributes to the development of e-commerce systems that are not only linguistically translated but also semantically tied to religious and cultural significance.

C. Pattern Libraries in Software Development

Pattern libraries offer a systematic approach to interface design, promoting consistency, efficiency, and reuse in software development. Puteri and Widyanti [4] claim that using pattern libraries reduces cognitive work while improving system predictability for users. Haque et al. [5] developed culturally relevant pattern libraries for Islamic systems, such as prayer times, modest fashion filters, and Halal certification widgets. Additional research by [11] and [12] demonstrates that culturally localising pattern libraries improves usability while also generating emotional trust, which is an important factor in religious technology acceptance. These findings emphasise the necessity of culturally appropriate UI components in Halal-oriented systems.

D. Lexical Mapping

Lexical mapping functions as a linguistic bridge, enabling accurate translation and classification across languages. This is especially important in Halal systems, because the meaning of terminology varies depending on the cultural, gastronomic, or religious setting. Lexical mapping normally consists of four components: word-level, phrase-level, context-specific, and morphological mapping [13].

1) *Word-level mapping*: This approach is based on one-to-one lexical equivalence. For example, "makan" translates to "أكل" (food), and "rumah" to "بيت" (house), setting the framework for basic vocabulary alignment.

2) *Phrase-level mapping*: Fixed expressions, such as greetings and frequent idioms, are represented using units. For example, "Selamat pagi" becomes "صباح الخير" (Good morning), while "Terima kasih" maps to "شكراً" (Thank you), while keeping semantic intent.

3) *Context-specific mapping*: Words with several meanings require context-sensitive disambiguation. The Malay word "masak" can mean "ripe" (ناضج) in the context of fruit or "to cook" (طبخ) in culinary usage, highlighting the necessity for sophisticated disambiguation algorithms.

4) *Morphological mapping*: This includes root-word relationships and affixes. For instance, "makanan" (meal) is derived from the root "makan" and the suffix "-an," resulting in "طعام." Similarly, "berjalan" (walking) breaks down into "ber-" and "jalan," which corresponds to "يمشي" in Arabic. This morphological intelligence is necessary for developing robust natural language processing (NLP) systems.

III. METHODOLOGY

To design, develop, and test the recommended food categorisation model, a proof-of-concept application was built by merging Machine Learning (ML) techniques with Malay-Arabic lexical analysis via Natural Language Processing (NLP) [14]. This methodological framework is separated into three major stages: parameter design, analysis, and testing, as follows:

A. Parameter Design

The parameter design phase of the study focuses on overall process flow and component integration, as illustrated in Fig. 1. The system architecture uses machine learning and rule-based analysis to identify whether a food item is halal or not. The

program parses Malay-language food descriptions, possibly translating them into Arabic for better semantic understanding, before assessing the content using a hybrid classification technique.

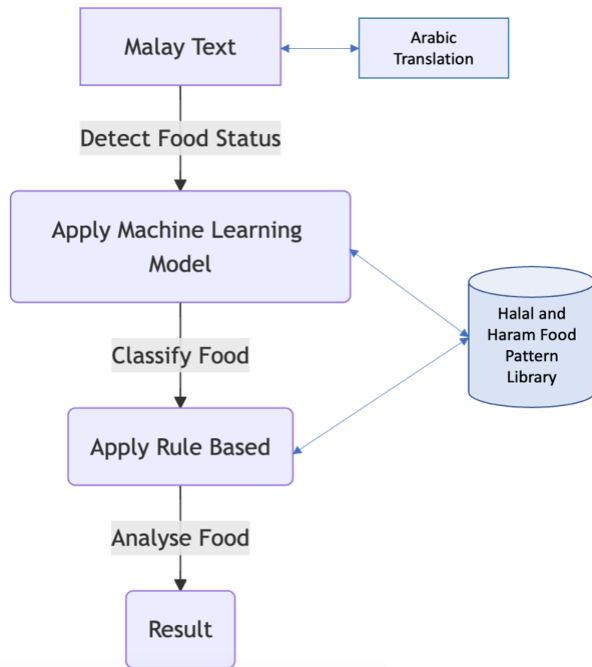


Fig. 1. Process activity for integrating machine learning and Malay-Arabic lexical mapping.

B. Parameter Selection

The Malay Arabic translation, machine learning model, and rule-based approach were considered when selecting parameters for this study. The particulars of parameter selection were explored in Fig. 2 as follows.

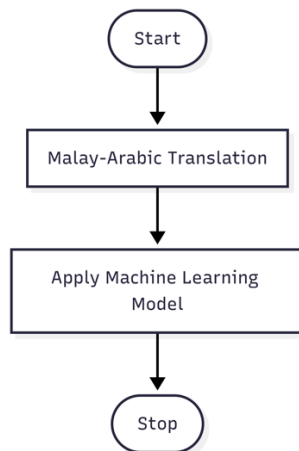


Fig. 2. Parameter selection.

1) *Malay to Arabic translation*: The system gets food-related text in Malay that needs to be evaluated. Consider "Daging ayam dengan alkohol" (alcoholised chicken meat). Finally, if necessary, the Malay text is translated into Arabic for better semantic understanding.

2) *Apply machine learning model*: The Machine Learning (ML) approach to categorising halal and haram foods consists of many key stages. Data collection and preprocessing begin with the compilation of a list of food names labeled as halal or haram according to Islamic dietary guidelines, followed by text preparation steps such as tokenisation, lowercasing, and special character removal, with words then transformed into numerical attributes using TF-IDF or word embeddings. Next, a Random Forest Classifier is used to increase accuracy by integrating numerous decision trees; this strategy takes advantage of classification and regression trees (CARTs) while reducing correlations between them [15].

During the model training and assessment phase, the dataset is separated into training (80%) and testing (20%) subsets, with the training data allowing the model to learn patterns and the testing data validating its predictive potential [16]. The model's performance is then evaluated using metrics such as accuracy, precision, recall, and F1-score: accuracy measures overall correctness, precision measures the proportion of correctly predicted positive cases, recall measures the ability to identify all actual positive cases, and the F1-score combines precision and recall to provide a balanced evaluation of performance [17].

3) *Apply rule-based*: A rule-based system uses established logical rules to classify and analyse data [18]. A rule-based approach for halal and haram food classification includes manually established rules, such as:

a) Keyword matching is the process of determining when a food item has halal or haram components by comparing its ingredients to a predetermined list of keywords. b) Simple criteria are employed to apply conditional logic, such as labelling a food as "haram" if it contains "babi" (pork) or "halal" if it contains "ayam" (chicken). This classification is based on the direct presence of specific terms. c) Natural language processing (NLP) is used to break down a sentence or meal description into individual words or tokens, which are then evaluated using predefined classification algorithms. This enables more effective handling of text input in many languages or unstructured formats. d) As the classification procedure progresses, decision trees are introduced.

C. Parameter Analysis

This section, as shown in Fig. 3, examines data collection or preparation, text pre-processing, random forest classifier training, and halal or haram phrase prediction, with the following details.

1) *Data preparation*: This structured dataset can serve as a foundation for machine learning models aimed at automatic halal food classification via natural language processing. Fig. 4 illustrates heatmaps comparing halal and haram classifications.

```
import pandas as pd
```

```
data = {"sentence": ["ayam", "gelatin babi", "susu", "alkohol",  
"daging lembu", "babi", "sayur-sayuran organik", "ikan", "babi",  
"biawak", "telur", "unta", "kambing", "renet", "lemak babi",  
"daging peha babi"]}
```

```
"label": [1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0]  
# 1 = Halal, 0 = Haram}  
df = pd.DataFrame(data)
```

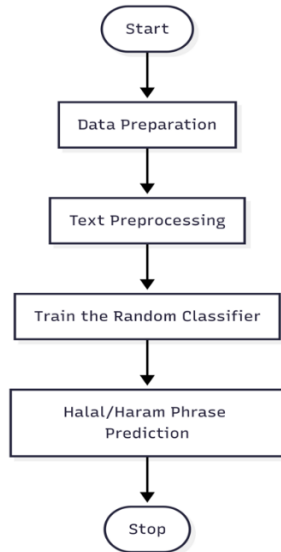


Fig. 3. Parameter analysis.

The collection contains 16 food-related items that have been classed as halal (permissible) or haram (forbidden) by Islamic dietary guidelines. Each item contains a food term (for example, "ayam", "gelatin babi", or "susu") and a binary label such as 1 for halal and 0 for haram. The data is stored in a pandas DataFrame, with column "sentence" containing the food's name or description and column "label" showing its classification. Eight of the 16 items are halal, including "ayam" (chicken), "susu" (milk), "daging lembu" (beef), and "ikan" (fish), while the remaining eight are haram, including "gelatin babi" (pork gelatin), "alkohol" (alcohol), "lemak babi" (pork fat), and "daging peha babi" (pork thigh meat). This structured dataset can serve as a foundation for machine learning models aimed at automatic halal food classification via natural language processing. Fig. 4 illustrates heatmaps comparing halal and haram classifications.

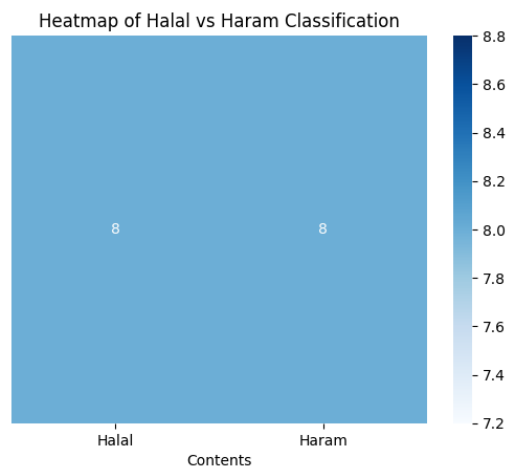


Fig. 4. Heatmaps of halal vs. Haram classification.

2) *Text preprocessing*: To prepare the data for machine learning, the TF-IDF vectorisation approach was used to convert text into numerical features. As a result, this Python technique is part of a pipeline that uses text classification to detect halal and haram food items. The data is separated into two categories: training (80%) and testing (20%). The following line explains how to utilise TF-IDF vectorisation to convert text into numerical attributes. Fig. 5 illustrates the steps for preparing text in code statements.

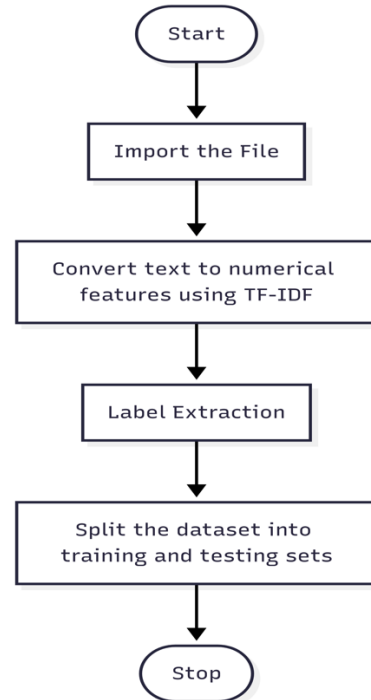


Fig. 5. Text preprocessing.

Based on Fig. 5, step 1, `TfidfVectorizer` from `sklearn.feature_extraction.text` turns text data into numerical representations that a machine learning model can process. The `train_test_split` from `sklearn.model_selection` partitions the dataset into training and testing sets for model evaluation. In Step 2, TF-IDF (Term Frequency-Inverse Document Frequency) is applied to the text data (`df["sentence"]`), turning words into numerical vectors representing their significance in the dataset. `Stop_words='english'` removes common words (such as "the" and "is") that do not contribute to classification. Step 3 extracts the label column, which contains binary categorisation values (1 for halal and 0 for haram). Finally, in Step 4, the dataset is partitioned into training (80%) and testing (20%) sets to assess model performance. This `random_state=42` ensures consistent splits across different runs, improving reproducibility.

3) *Train the random forest classifier*: The Random Forest model was trained and tested on pre-processed text data with scikit-learn for text categorisation. The purpose is to identify food items as halal or haram based on textual descriptions. Fig. 6 depicts the Random Forest Classifier training.

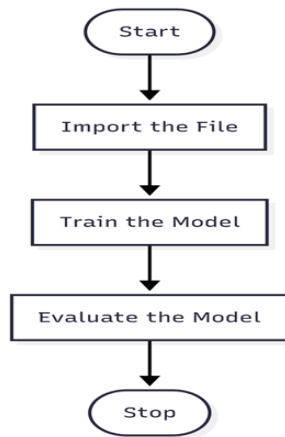


Fig. 6. Random forest classifier training.

Based on Fig. 6, step 1, RandomForestClassifier is imported from sklearn.ensemble. It is an ensemble learning technique that use numerous decision trees to boost classification accuracy. The accuracy_score from sklearn.metrics is used to assess the model's performance by determining the proportion of correctly categorised labels. In Step 2, n_estimators equal 100: The model generates 100 decision trees, with the final classification depending on the majority vote of these trees. The random_state is 42: Fixes the random seed to ensure reproducibility. The model is trained on the training dataset (X_train, y_train), learning patterns from text-based features extracted by TF-IDF. Finally, in Step 3, the trained model predicts the class labels (halal or haram) for an unknown test dataset (X_test). The model's accuracy is calculated by comparing predicted labels (y_pred) to actual labels (y_test). Accuracy is expressed as a decimal value (for example, 0.85 for 85%). Displays the accuracy score rounded to two decimal places.

4) *Prediction on halal or haram sentences:* The sentences or words are classified using the trained model based on the following Algorithm 1.

Algorithm 1: Sentences or words classification for prediction, Halal or Haram algorithm

```
Initialize
Compute
def classify_food (sentence):
    predictions = []
    sentence_transformed = vectorizer.transform([sentence])
    predicts[count] = model.predict(sentence_transformed)
    print (f"ML- predict: {predicts}")
    count = count +1
if 0 in predicts:
    return "HARAM"
else:
    return "HALAL"
```

D. Parameter Testing

Parameter testing is necessary during implementation to optimise the Random Forest classifier's performance. Several important factors were meticulously altered and assessed to determine the best model design, as shown in Table I. First, the

n_estimators parameter, which controls the number of decision trees in the forest, was tested for values ranging from [10, 50, 100, 200]. The trials found that increasing the number of estimators improved model stability and accuracy, with 100 trees providing a good balance of performance and processing efficiency. As a result, the final model used n_estimators = 100. The max_depth option, which determines the maximum depth of each tree, was tested with values of [5, 10, 15, None]. A depth of 15 was identified to appropriately reflect the data's complexity while preventing overfitting, which occurs when no limit (None) is used. The min_samples_split and min_samples_leaf variables were also useful for refining the model. Testing settings for min_samples_split as [2, 5, 10] and min_samples_leaf as [1, 2, 5] revealed that the default values of 2 for split and 1 for leaf resulted in better generalisation, keeping the model's flexibility while avoiding excessive splits that could lead to overfitting. The criterion parameter, which describes the function used to determine the quality of a split, was compared to both 'gini' and 'entropy'. The 'gini' index was chosen since it gave somewhat better performance and faster processing in this scenario. Finally, to ensure reproducibility, random_state=42 was kept constant throughout the tests. The final optimised model, which included these parameters, was trained using TF-IDF-transformed training data (X_train, y_train) and tested against test data (X_test, y_test). The printed end accuracy demonstrated that the chosen criteria resulted in a strong and accurate classification system for discriminating between "Halal" and "Haram" food items. The parameter setting is demonstrated in Algorithm 2 for RandomForestClassifier.

Algorithm 2: Parameter Testing for RandomForestClassifier

```
Initialize
Compute
optimized_rf = RandomForestClassifier(
    n_estimators=100, max_depth=15, min_samples_split=2,
    min_samples_leaf=1, criterion='gini', random_state=42)
optimized_rf.fit(X_train, y_train)
y_pred = optimized_rf.predict(X_test)
final_accuracy = accuracy_score(y_test, y_pred) print("Final
Optimized Random Forest Accuracy:", final_accuracy)
```

TABLE I. TESTING N_ESTIMATORS (NUMBER OF TREES)

Parameter	Description	Value to Test
n_estimators	Number of decision trees in the forest	10, 50, 100, 200
max_depth	Maximum depth of each decision tree	5, 10, 15, None
min_samples_split	Minimum number of samples required to split a node	2, 5, 10
min_samples_leaf	Minimum samples required in a leaf node	1, 2, 5
criterion	Function to measure the quality of a split	'gini', 'entropy'

During implementation, the code is based on parameter selection and testing, and is designed to categorize food products for "Halal" or "Haram" using a set of phrases and labels. Then, the text input is converted into numerical characteristics for categorisation using machine learning (ML), a Random Forest classifier, and TF-IDF vectorisation. Algorithm 2 shows how the

ML model is trained using the sentences. After that, the accuracy is checked. Halal and haram foods and make recommendations for halal products is identified using a rule-based system. Google Translate to translate Malay API is used in a code, as well as machine learning and rule-based analysis to classify meals and provide halal alternatives. The application also shows how both methods can be used to categorise and recommend food items.

This study introduces a novel integration of Malay–Arabic lexical mapping into machine learning–based Halal food classification, a combination that has not been previously explored in existing literature. While prior studies have focused on single-language (Malay or English) Halal text classification, this research leverages bilingual semantic alignment between Malay and Arabic to enhance contextual understanding of religious terminology in ingredient lists. Furthermore, the application of the Random Forest classifier within this multilingual, culturally grounded framework represents a methodological advancement, as it enables higher interpretability and robustness compared to conventional models such as Naïve Bayes and SVM. The framework's strength lies in its ability to connect cultural linguistics and AI-driven food classification, resulting in a system better aligned with Islamic dietary principles and real-world e-commerce applications.

IV. RESULTS

The study findings are separated into three categories which are TF-IDF Score analysis, Comparison of Performance analysis, and Precision, Recall, and F1-Score for Halal Food Malay-Arabic.

A. TF-IDF Score Analysis

Fig. 7 shows the TF-IDF heatmap, which visualises term importance across a variety of food-related texts. The heatmap illustrates the frequency and significance of specific words in the dataset, with darker hues (red) suggesting higher importance and lighter tints (blue) indicating lower relevance. This Figure is essential for understanding the distinction between halal and haram foods. Example keywords such as "babi" (pork) and "alkohol" (alcohol) have higher TF-IDF values in haram sentences, indicates that they are commonly employed to discriminate against prohibited products. Similarly, terms such as "ayam" (chicken) and "ikan" (fish) have high TF-IDF scores in halal-classified phrases, emphasising their importance in identifying permissible food products. The dataset's structure reveals that some terms are more distinctive, whilst others appear often in several sentences, resulting in lower TF-IDF scores. This graphic effectively underlines which words contribute the most to the categorisation process in a machine-learning model [19]. However, while the heatmap depicts word relevance, it has several disadvantages. Such as TF-IDF does not capture word context. Instead, it uses frequency-based weighting, which may not fully reflect real-world nuances in halal-haram classification [20]. For example, the term "daging" (flesh) can be halal or haram depending on the context, but TF-IDF cannot tell the difference. Furthermore, the heatmap's readability could be improved by sorting phrases by relevance or clustering related words. Combining TF-IDF with additional advanced NLP techniques, such as word embeddings or transformers, may increase classification accuracy by capturing

deeper semantic connections [21]. Recent research indicates that deep learning models can outperform TF-IDF in halal food classification by analysing ingredient texts with contextual embeddings [22].

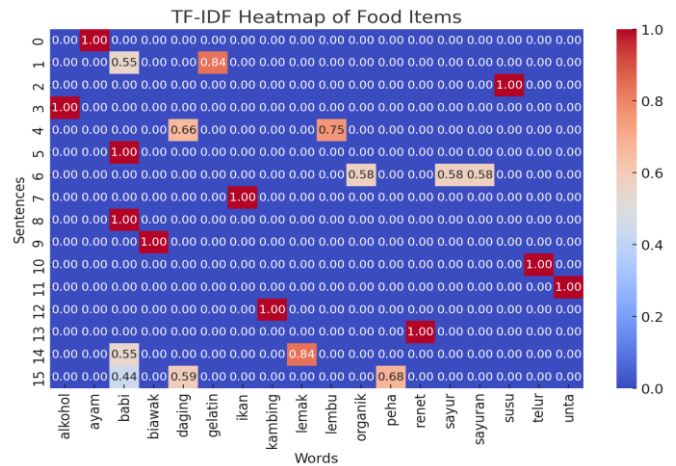


Fig. 7. TF-IDF of food items.

B. Performance Analysis

Fig. 8 compares Random Forest, Naïve Bayes, SVM, and Logistic Regression in terms of accuracy and training time.

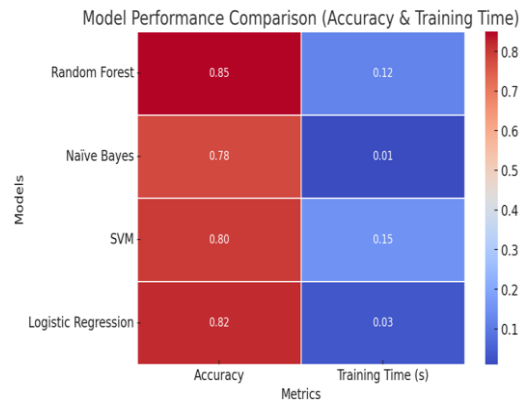


Fig. 8. Comparison of performance analysis.

According to Fig. 8, a comparison of machine learning models for halal-haram classification shows that Random Forest has the highest accuracy (85%), making it the most reliable alternative. However, it has a moderate training time of 0.12 seconds, which is longer than simpler models like Naive Bayes (78% accuracy, 0.01s training time). The fastest model, Naive Bayes, is effective for quick classifications but lacks accuracy. Meanwhile, SVM (80% accuracy, 0.15s training time) performs admirably but takes the longest to learn. Logistic Regression (82% accuracy, 0.03s training time) achieves a balance of efficiency and interpretability, but it may struggle with complicated patterns.

C. Precision, Recall, and F1-Score for Halal Food Malay-Arabic

To assess the effectiveness of the proposed halal food classification system, particularly with the addition of Malay-Arabic lexical mapping, four machine learning models were

tested using three major classification metrics: precision, recall, and F1-score. Fig. 9 presents these variables as heatmap comparisons, which allows for an easier assessment of model performance across several evaluation criteria.

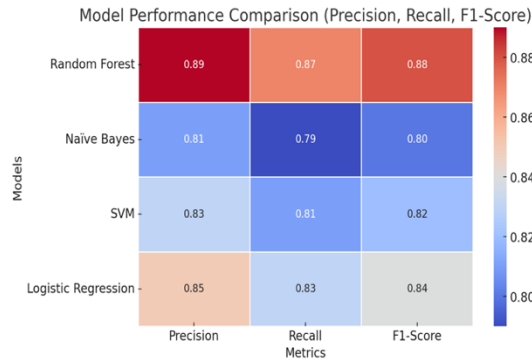


Fig. 9. Precision, recall, and F1-score.

Naive Bayes produces reasonable results (Precision: 0.81, Recall: 0.79, F1-Score: 0.80), indicating that, while it works adequately, it cannot generalise as well as Random Forest. Support Vector Machine (SVM) improves recall (0.81) and balance (F1-Score: 0.82) but falls short on precision (0.83), possibly due to its sensitivity to overlapping classes. Logistic Regression has a high precision (0.85) and a decent recall (0.83), yielding an F1-score of 0.84, indicating balanced but slightly poorer performance than Random Forest.

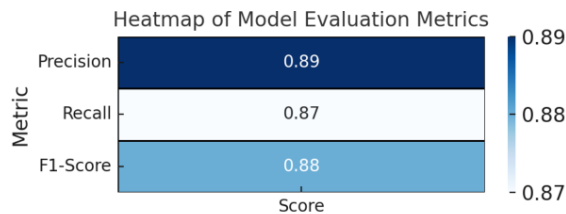


Fig. 10. Output of model evaluation metrics.

Fig. 10 demonstrates that the Random Forest model outperforms all three metrics. These high scores demonstrate that Random Forest properly identifies halal/haram classes (precision) while also catching the vast majority of actual positive examples (recall), yielding an exceptional balance (F1-score). This result indicates the model's stability and dependability in this classification job, especially when supplemented with lexical mapping between Malay and Arabic terminologies, which aids in the resolution of semantic ambiguities in food ingredients and naming traditions.

V. DISCUSSIONS

Overall, Random Forest is the most reliable and accurate classification model, making it ideal for practical halal food identification. Naïve Bayes provides the fastest performance, while Logistic Regression balances accuracy and efficiency. SVM, while accurate, is slower and requires more computing power. The model chosen is based on the application's specific requirements, such as accuracy, speed, and interpretability [23][24]. These findings suggest that Random Forest is the most effective classifier for the Malay-Arabic halal food classification problem. Lexical mapping significantly enhances the semantic

comprehension of ingredient lists by connecting culturally and religiously significant phrases in Malay and Arabic, such as recent studies by Khalilia et al. [25] demonstrate the creation of cross-lingual maps via a supra-lingual concept layer that can account for culturally unique terms that lack direct counterparts in other languages. This linguistic enrichment allows the model to discover minor distinctions that are critical in halal food assessment, hence boosting both the classification system's accuracy and cultural context [26]. Thus, combining machine learning and multilingual lexical analysis improves performance metrics while also aligning the system with real-world requirements in various Muslim-majority or multilingual regions.

VI. CONCLUSIONS AND FUTURE WORK

This study emphasises the need to implement AI-powered technologies to improve Halal e-commerce platforms. Using machine learning classification models and lexical mapping methodologies, the system accurately detects Halal items while retaining their linguistic and cultural significance. The study found that combining pattern libraries, multilingual support, and advanced text processing significantly enhances usability, accessibility, and trust among Muslim consumers. The Random Forest model, achieving a maximum accuracy of 85% outperforming the baseline models by up to 10%, proved to be the most effective Halal-Haram classifier. The proposed framework lays the groundwork for future developments in Halal digital commerce, ensuring Islamic compliance while leveraging modern technological advancements. However, several limitations must be acknowledged. The dataset size used in this study is relatively limited, which may constrain the model's ability to generalize to broader food categories. Additionally, potential data bias in labeled samples and restricted language coverage, such as being focused mainly on Malay and Arabic that may affect the model's accuracy and cultural inclusiveness in wider contexts. Future research should therefore aim to expand multilingual datasets, address bias through balanced sampling, and improve NLP capabilities to enhance classification accuracy and contextual understanding. Moreover, integrating real-time certification verification with blockchain technologies, as well as an e-Commerce framework, could improve transparency and traceability in Halal authentication. Collaboration with Halal certification authorities and e-commerce providers will also be vital to standardize digital Halal verification procedures. Ultimately, this study contributes to the growing field of Halal e-commerce by paving the way for safer, more efficient, and culturally inclusive online markets, such as helping to eliminate doubtful Halal products and build greater consumer trust.

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REFERENCES

- [1] N. Saleem, A. Khalid, and S. Sadiq, "Impact of e-commerce on Consumer Behavior: A Study of Online Shopping Trend among Youth in Lahore

- City,” Ashwin Anokha Publications & Distributions, 2022. [Online]. Available: <http://www.ashwinanokha.com/IJEB.php>.
- [2] S. L. Nurillah, “The Importance of Halal Certificates in Halal Food Using the Digital Platform,” *Int. J. of Law Dynamics Review*, vol. 1, no. 2, Nov. 2023, pp. 99–111.
- [3] D. Yener, “The Effects Of Halal Certification And Product Features On Consumer Behavior,” *Int. J. of Management Studies*, vol. 29, 2022.
- [4] R. Puteri and A. Widyanti, *E-commerce of Islamic fashion product: usability and user acceptance*. 2018.
- [5] S. Haque, “Language Use and Islamic Practices in Multilingual Europe,” 2025. [Online]. Available: <https://www.cambridge.org/core>.
- [6] M. Mabruh and R. Khoiriyah, “Islamization of Malay Language and its Role in the Development of Islam in Malaya,” *AJIS: Academic Journal of Islamic Studies*, vol. 4, no. 1, Jul. 2019, p. 13.
- [7] M. S. Mazli, “Deep learning-based halal food recognition,” 2020.
- [8] S. Tarannum, M. S. Jalal, and M. N. Huda, “HALALCheck: A Multi-Faceted Approach for Intelligent Halal Packaged Food Recognition and Analysis,” in *IEEE Access*, vol. 12, 2024, pp. 28462–28474.
- [9] A. M. Ahmad et al., “Ensuring halal food integrity: An overview of modern molecular and technological solutions,” *Food Biomacromolecules*, vol. 2, 2025, pp. 5–22.
- [10] B. Hutchinson, “Modeling the Sacred: Considerations when Using Religious Texts in Natural Language Processing,” in *Findings of the Association for Computational Linguistics: NAACL 2024*, Mexico City, Mexico, June 2024, pp. 1029–1043.
- [11] K. Zurida Ishak, and A. Jaafar, “Cultural Dimensions of Malaysian Teenagers and Their Relationship with Interface Design,” *J. Theor. Appl. Inf. Technol.*, Vol. 90, No.2 (2016), pp. 176–186.
- [12] S. M. Z. Samsuri, S. A. Ariffin, and N. S. Fathil, “Incorporating Cultural Design Elements in Mobile Applications Creative Industries in Malaysia: A Conceptual Study,” *J. ICT in Education*, Vol. 8 No.2 (2021), pp. 110–117.
- [13] A. François, “Lexical tectonics: Mapping structural change in patterns of lexification,” *De Gruyter*, vol.41. no.1, 2022, pp.89–123.
- [14] D. Alfter, “Complexity and Indecision: A Proof-of-Concept Exploration of Lexical Complexity and Lexical Semantic Change,” 2024.
- [15] Z. Sun, G. Wang, P. Li, H. Wang, M. Zhang, and X. Liang, “An improved random forest based on the classification accuracy and correlation measurement of decision trees,” *Expert Syst Appl*, vol. 237, Mar. 2024.
- [16] V. Roshan Joseph, “Optimal Ratio for Data Splitting,” *Statistical Analysis and Data Mining*, Feb. 7, 2022.
- [17] S. Sathyanarayanan, and B. Roopashri Tantri, “Confusion Matrix-Based Performance Evaluation Metrics,” *Afr. J. Biomed. Res.*, vol. 27, no. 4s, Nov. 2024, pp. 4023–4031.
- [18] Z. Wang, J. R. Talburt, N. Wu, S. Dagtas, and M. N. Zozus, “A Rule-Based Data Quality Assessment System for Electronic Health Record Data,” *Appl Clin Inform*, vol. 11, no. 4, Aug. 2020, pp. 622–634.
- [19] F. Tobing, H. Fauzan, K. Simatupang, and R. Aulia, “The Role of Artificial Intelligence in the Halal Industry,” *Information Management and Business Review*, vol. 16, no. 3(I)S, Sept. 2024, pp. 159–166.
- [20] L. Kalyani, M. Jacintha, D. Kar, N. Roy, and V. K. Sharma, “A Comparative Analysis of Text Embeddings (TF-IDF, Word2Vec, FastText) for Machine Learning-Based Fake News Detection,” *Int. J. Eng. Res.*, vol. 11, no. 6, June 2024, pp. a760–a763.
- [21] F. Rifaldy, Y. Sibaroni, and S. Suryani Prasetyowati, “Effectiveness of Word2Vec and TF-IDF in Sentiment Classification on Online Investment Platforms Using Support Vector Machine,” *J. Penelitian dan Pembelajaran Informatika (JIPI)*, Mar. 2025.
- [22] A. D. Bhargavi, “Comparative Study of Static and Contextual Text Vectorization for Sentiment Analysis,” *International Journal for Research in Applied Science & Engineering Technology*, 2025.
- [23] A. J. Wyner, S. J. Bleich, D. M. Olson, and B. Mease, “Explaining the Success of AdaBoost and Random Forests,” *Journal of Machine Learning Research*, vol. 18, 2017, pp. 1–40.
- [24] H. Ahmed Salman, A. Kalakech, and A. Steiti, “Random Forest Algorithm Overview,” *Babylonian J. of Machine Learning*, vol. 2024, pp. 69–79, 2024.
- [25] A. Khalilia et al., “Crowdsourcing lexical diversity: Mapping language-specific concepts into a supra-lingual semantic layer,” *ACM Trans. Asian Low-Resour. Lang. Inf. Process.*, vol. 37, no. 4, Article 111, Sept. 2024.
- [26] N. Yusop, M. Kamalrudin, N. A. Mokhtar, and N. Mustafa, “The role of language in Malaysia’s halal food industry: Trends, challenges, and future directions,” *Int. J. Res. Innov. Soc. Sci.*, vol. 9, no. 2, Feb. 2025, pp. 437–445.