Harmonizing the Plate: AI-Driven Halal Compliance for tourism

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Abstract

The global Halal tourism sector is expanding day by day, yet Muslim travelers face many challenges in verifying food compliance due to complex supply chains and the lack of universal certification. Our project, "Harmonizing the Plate," addresses these barriers by developing an AI-powered ingredient verification system to assist decision-making where official logos are absent. The study utilizes a hybrid classification methodology combining a list of known additives (E-codes) with a Deep Learning model for natural language interpretation. Using two dataset of 39,573 ingredients, we trained a Bidirectional LSTM (Long Short-Term Memory) neural network to analyze textual ingredient lists, supported by Tesseract OCR for visual label scanning. The system parses complex ingredient strings, cross-referencing a verified knowledge base for immediate accuracy while employing the LSTM model to predict the status of ambiguous items. Results demonstrate that this hybrid approach effectively identifies Halal, Haram, and Mushbooh ingredients with a "safety-first" logic. This solution enhances transparency and convenience for Muslim consumers, effectively bridging the gap in global Halal assurance

Introduction

The global Halal tourism sector represents a massive, high-growth economic opportunity, yet its expansion is severely limited by critical food compliance issues. Academic research consistently identifies the availability of Halal food as the single most important factor for Muslim tourists when selecting a travel destination. As this user segment grows, there is an increasing demand for trust and convenience to travel confidently without compromising religious obligations. The purpose of this research is to address the logistical challenges within the modern food supply chain that hinder Muslim travelers from easily accessing compliant food products in non-Muslim majority regions..

The core problem identified is the global "Certification Gap," defined by the lack of standardized, universal Halal certification and the insufficiency of relying solely on external logos. Many products consumed by travelers lack official certification, forcing consumers to check complex ingredient lists manually. This challenge is compounded by modern food processing, where ingredients like gelatin, enzymes, or emulsifiers often possess an ambiguous Halal status (*Mushbooh*). Existing solutions, such as manual checking or logo-based apps, often lack the intelligence to interpret these complex ingredient variations accurately and are difficult to apply in real-time.

In the context of data science and analytics, this is a Classification Problem, which is a subset of Predictive Analytics ("What is likely to happen?"). The task involves processing unstructured textual data specifically food ingredient lists to predict a categorical label for each item: *Halal*, *Haram*, or *Doubtful* (*Mushbooh*). The model predicts the "likely" status of an ingredient based on learned patterns from a training dataset.

This problem exists within the International Business and Tourism domain. It specifically targets the global Halal food market, addressing consumer behavior and decision-making friction. The solution aims to facilitate smoother transactions and increase sales for international food retailers by removing the uncertainty that prevents Muslim consumers from purchasing uncertified products.

The research problem is best understood through the scenario of a Muslim traveler shopping in a foreign country like China where local products may not carry a recognized Halal logo. To solve this, we propose "Harmonizing the Plate," which functions as an AI-powered Classification System. When the user encounters a product with an unfamiliar label. Instead of manually searching for each chemical additive, the user takes a photo of the ingredient list using the app. The system utilizes Optical Character Recognition (OCR) to extract text from the image and applies a Deep Learning model to analyze the ingredients.In result, the app will classifies the ingredients and provides an instant "Halal" or "Mushbooh" verdict, allowing the consumer to make an informed purchasing decision immediately.

Background

The main classification engine for our project is utilizing Long Short-Term Memory (LSTM) networks which is specialized architecture of Recurrent Neural Networks (RNNs). Originally introduced by Hochreiter and Schmidhuber in 1997, LSTMs were designed to overcome the "vanishing gradient" problem that plagued traditional RNNs, preventing them from learning dependencies in long sequences of data. LSTMs address this through a unique internal structure composed of "memory cells" regulated by three distinct gates which are the input gate, the output gate, and the forget gate. These gates control the flow of information, deciding which data to retain and which to discard over time. For this project, we specifically implemented a Bidirectional LSTM, which processes the ingredient text in both forward and backward directions simultaneously. This bidirectional approach is critical for accurate Halal classification, as it allows the model to capture full contextual dependencies. for example, ensuring that a modifier like "pork" at the beginning of a string is correctly associated with a noun like "gelatin" at the end.

To enable the LSTM model to interpret human language, we employed Natural Language Processing (NLP) techniques, specifically Word Embeddings. Since neural networks cannot process raw text directly, NLP converts linguistic data into numerical vectors. In this system, we utilized the Keras Embedding layer to map integer-encoded ingredient lists into dense vectors of real numbers. Unlike simple one-hot encoding, word embeddings place words with similar semantic meanings closer together in the vector space. This is essential for the "Harmonizing the Plate" system because it allows the model to learn relationships between ingredients without explicit hard coding. For instance, the model can learn that terms like "lard," "tallow," and "suet" are semantically related and should likely share the same "Haram" or "Doubtful" classification,silmutaneously improving the model's ability to generalize to unseen data.

To bridge the gap between physical product packaging and our digital classification model, the system integrates Optical Character Recognition (OCR) technology, which is Tesseract OCR engine. Originally developed by Hewlett-Packard and currently maintained by Google, Tesseract utilizes pattern matching and feature extraction to identify characters within digital images. In our application workflow, OCR serves as the primary data ingestion point. When a user take picture of product label, the OCR engine analyzes the pixel data to identify lines, words, and individual characters, converting the visual image into a raw string of text. This extracted text is then cleaned and passed to the NLP pipeline for tokenization and classification, enabling a seamless user experience where complex ingredient analysis can be performed instantly from a simple smartphone photograph.

Problem Statement

The core challenges that lead us to make this research is the significant difficulty of Muslim travelers face in adhering to dietary laws while navigating non-Muslim majority regions. With the rise of global tourism, many Muslim travelers visit destinations such as Türkiye, China, or Europe, where access to compliant food is often restricted by language barriers and labeling ambiguities. The primary issue is the reliance on traditional visual verification that make the consumers typically look for an official Halal logo to ensure a product is safe to consume. However, this method is increasingly insufficient in the modern global market. A vast number of permissible (Halal) products do not carry certification due to the high costs or logistical complexities of the certification process, creating a "Certification Gap".

Furthermore, existing digital solutions fail to solve this gap. Most current Halal tracker applications rely exclusively on static databases of official certifications such as JAKIM and MUI. While useful within specific regions like Malaysia, these databases are geographically limited and often fail to recognize identical products sold in different countries with varying ingredients. Consequently, when a product lacks a logo or is absent from a certification database, the consumer is left with no recourse but to manually decipher complex ingredient lists. This process is prone to error, particularly regarding ambiguous chemical additives (Mushbooh) or scientific nomenclature that requires specialized knowledge to interpret. Thus, there is a critical need for an intelligent, ingredient-based system capable of analyzing the "DNA" of a product's label rather than simply searching for a certification stamp

Research Question and Hypothesis

A. Research Question

- Is there a any correlation between the transparency of Halal status in packaged products (independent variable) and Muslim consumers' purchasing behavior (dependent variable)?
- How does emphasizing AI-powered Halal Tracker affect decision-making process, specifically regarding speed and accuracy among Muslim consumers?

B. Hypothesis

- If the transparency of ingredient Halal status increases, Muslim customers confidence level will increases too in their purchasing decisions, positively affecting their buying behavior.
- By utilizing an AI-powered Halal Tracker, Muslim consumers will able to identify product Halal status more easily, quicker and makes more accurate shopping decisions compared to manual verification methods

Research Objective

- To develop and train a machine learning model, leveraging Deep Learning and Natural Language Processing (NLP) techniques to capable of accurately classifying food ingredients and menu items into Halal, Haram, or Mushbooh categories.
- To evaluate the finalized model's robustness and generalizability by testing its performance against many datasets, to ensure it can handles real-world variations in ingredient labeling.

Research Significances

- To enhance customer confidence and convenience by providing Muslim travelers with "peace of mind" and trust when purchasing food abroad. By providing an instant, transparent assessment of food ingredients, the system empowers consumers to make quicker and more accurate decisions, eliminating the hesitation caused by ambiguous ingredients.
- Solving the "Certification Gap" by offering a scalable solution that does not rely on costly official certification processes. This unlocks a wider range of food options for Muslim consumers that are compliant but not officially certified.
- Boosting the Halal food industry economy by removing the friction of food compliance which make international travel more accessible and enjoyable for the Muslim demographic, potentially increasing tourism spending in non-Muslim majority destinations.
- Promote Technological Innovation in Islamic perspective by applying the application of advanced AI (Deep Learning and OCR) to solve a religious compliance issue. It moves beyond simple database lookups to intelligent interpretation, setting a precedent for how technology can be used to "harmonize" modern global consumption demands with strict religious obligations.

Islamic Overview (Perspectives from Shariah)

- Preservation of Religion (*Hifz al-Din*):
  - The project maintain preservation of religion by enabling Muslim travelers to adhere to strict dietary laws (*Halal* and *Haram*) even when in non-Muslim majority regions where compliance is difficult.
  - It helps muslim travler avoid consuming prohibited items (*Haram*) and protects them from compromising their religious obligations due to ignorance or language barriers.
- Avoiding the Doubtful (*Ijtinab al-Shubahat*):
  - A main target of the system is to identify "Mushbooh" (doubtful) ingredients, such as ambiguous chemical additives or emulsifiers.
  - This objective aligns with the hadith which is "leaving what is doubtful for what is clear", as the AI acts as a tool to clarify the status of ambiguous ingredients.
- Establishing Certainty (*Yaqin*):
  - The tool aims to remove *mushbooh* (doubt) and *Wahm* (conjecture) from the consumer's thinking, replacing it with data-driven certainty regarding the ingredients they are about to consume.
  - It moves the verification process from "guessing" to "informed decision-making"

LITERATURE REVIEW

Year	Authors / Title (short)	Research problem	Main techniques applied	Main results	Future works / notes
2024	Fathima et al., “Advanced Halal Authentication Methods and Technology for Addressing Non-Compliance Concerns in Halal Meat and Meat Products Supply Chain: A Review”	How to authenticate halal status of meat and meat products across the supply chain to address non-compliance concerns (improper slaughtering, mislabeling, adulteration, contamination).	Reviews chemical, spectroscopic, sensor-based, and AI / ML methods for halal authentication., categorization of analytical methods by four non-compliance concerns (improper slaughter, mislabeling, adulteration, contamination).	Identified a high mislabeling rate of 78.3% in the samples - The type of slaughter affects ($p<0.05$) physiological parameters in blood samples, including glucose, lactate dehydrogenase, creatine kinase, and cortisol.	Recommends: 1. Calls for integrated AI systems, better datasets and standardization, and more explainable solutions. 2. Expanding methods for slaughtering and mislabeling evaluation 3. Integrating advanced technologies like biosensors, e-noses, AI and blockchain to improve traceability, transparency and supply-chain oversight.

2024	Jalal, M. S., et al. “HALAL Check: A Multi-Faceted Approach for Intelligent Halal Packaged Food Recognition”	Difficulty to recognize a Halal status of a product in unfamiliar environments.	The system uses a camera-based scannings to find food labels and smart text recognition to read the full ingredients of a product.	Achieved 98% accuracy in identifying Halal and Haram ingredients on packages.	Adding a community feature so that users can report if there any new products are available.

2019	Elfakharany, A., et al., "HalalNet: A Deep Neural Network That Classifies the Halalness of Slaughtered Chicken from Their Images"	Automated verification of Halal slaughtering compliance to replace error-prone manual inspection.	The researchers developed a deep neural network named HalalNet where it utilizes the Xception architecture for the purposes of one-shot learning on images.	It successfully classified Halal vs Non-Halal slaughter cuts by using high accuracy although it have small datasets.	Suggest real-time video monitoring in slaughterhouse
2019	Fatawi et al,. "Linked Open Data for Halal Products"	Fragmented Halal data across various international certification bodies.	The techniques involves using Linked Open Data(LOD) frameworks to integrate multiple data sources using semantic web technologies.	Integrated data from 7 international bodies into a single, unified verification dataset.	The goal is to create a worldwide "Global Halal Data Hub"

2021	Rakhmawati & Jannah, "Food Ingredients Similarity Based on Conceptual and Textual Similarity"	Linguistic ambiguity and differences in ingredient names (synonyms) among international mars.	Uses string matching techniques including Fuzzy String Matching and Levenshtein Distance to standardize ingredient classification.	Improved the matching of ingredient names across disparate international food databases.	Recommends: 1. Combining string matching with neural embeddings.
2020	Akram et al,. "OCR and Barcode based Halal and Health Analyzer"	Helping Muslim travelers identify food status where official Halal logos are absent.	Utilizes Tesseract OCR and barcode scanning algorithms to extract the ingredient strings and cross-reference them against a rule-based expert database.	Successfully identified 89% of Mushbooh or in other word doubtful ingredients in packaged goods or products.	Suggested moving to Deep Learning like LSTM for better context analysis.

2023	Tarannum, S., “Halal Food Identification from Product Ingredients using Machine Learning”	Address the difficulty of locating and verifying Halal-certified foods for travelers in unfamiliar markets where the Halal logos are absent.	Utilizes YOLOv5 for ingredient detection on packaging and followed by Tesseract OCR and a combination of Artificial Neural Networks(ANN) and fuzzy logic for classification.	Successfully automated the identification of Halal vs Haram status from packaging images and provide a scalable tool for mobile customers.	Recommends integrating real-time multilingual translation for global applicability.
2022	Fauzi, M. S., et al., "Ingredient Classification for Halal Products Using Pre-trained BERT Model"	Limitations of traditional machine learning (like LSTM/SVM) in understanding the context of complex ingredient names (polysemy).	Applied Bidirectional Encoder Representations from Transformers (BERT) to understand the semantic context of ingredient lists rather than just keyword matching.	Outperformed traditional models with an F1-score of 92%, showing superior capability in handling ambiguous ingredient terms.	Suggests fine-tuning the BERT model with a larger, domain-specific dataset (Malay/Arabic/English mixed) to improve multilingual accuracy.
2024	Sunmola, F., et al., “Holistic Framework for Blockchain-Based Halal Compliance in Supply Chains Enabled by Artificial Intelligence”	The issue of fragmented and lack of trust in ingredient provenance throughout the supply chain.	This study proposes an integrated framework utilizing Knowledge Graphs, Machine Learning-based text classification and Blockchain Smart Contracts to automate compliance.	Demonstrated that AI can automated the pre-certification process by identifying irregularities in sourcing before a product reaches the shelf.	Recommends exploiting Large Language Models(LLMs) to generate natural language explanations for classification outputs.
2023	Rahman, M. A., et al., "Mobile-Based Halal E-Code Detector for International Travelers"	Difficulty for Muslim tourists to memorize or identify non-Halal food additives (E-codes) on foreign food labels.	Utilizes Mobile Vision API for text recognition combined with a Boyer-Moore string matching algorithm to search a dedicated E-code database.	The application achieved a 95% success rate in detecting E-codes from curved packaging surfaces and instantly flagging them as Halal, Haram, or Syubhah.	Recommends incorporating Augmented Reality (AR) to overlay the Halal status directly on the product packaging screen.

By looking over the 10 studies from 2019 to 2024, it is clear that many academics have been researching the use of technology or Artificial Intelligence to confirm and verify the Halal status of food products. Most of them used OCR tools like Tesseract to read labels and many others applied machine learning models like ANN to classify ingredients. For supply chain transparency, some researchers even investigated blockchain. However, based on what we seen, there are still some important gaps. For example, many systems only rely largely on pre-existing certification databases which can be problematic when items are not formally certified and they only function well enough in one language which is English. Furthermore, few studies shown that they have integrated AI and rule-based verification in a way that prioritizes caution for doubtful ingredients. Additionally, very few expressly addressed the needs of Muslim travellers who often face language barriers and unfamiliar labels. That is precisely where our project can help.

Our project tries to fill in these gaps with a few key improvements. Firstly, instead of just using database or AI, we combined both which are the verified list of E-codes and additives with a Bi-LSTM model to handle new or ambiguous ingredients. We can both be precise and cautious thanks to our hybrid method particularly when it comes to "Mushbooh" items which we carefully mark to prevent errors. Secondly, we took Muslim travellers into consideration when designing everything. The software is quite helpful in locations without Wi-Fi or internet because it allows you to just take a picture of a label on the food ingredients and it will works even if you are offline.

METHODOLOGY

The methodology in this project will be a combination approach of integrating deterministic rule-based matching and prediction model with deep learning to classify the Halal status of food ingredients. The project pipeline is structured into data acquisition, preprocessing, model development, and system integration.

A. Dataset and Sources

The model uses two different datasets to ensure both accuracy and broad coverage:

1. Knowledge Base (Rule Book) Database: The file FOOD_ADDITIVE_LISTING_5.csv is used as the primary source for verified additives, includes E-codes and chemical names with their corresponding Halal or Doubtful status.

   https://www.ecodehalalcheck.com/

2. Training Dataset: The Ingredients.csv file, sourced from Kaggle, provides an immense corpus of ingredient labels and their classifications for training the neural network.

   https://www.kaggle.com/datasets/irfanakbarihabibi/food-ingredients-dataset-with-halal-label?resource=download

3. Data Refinement: The datasets were combined with removing duplicate data, ensuring data integrity. To optimize training performance, the final training set was sampled to a maximum of 50,000 rows out of 500, 000 rows.

B. Development Tools

This project uses python programming language and the following tools:

1. Scikit-learn: For traditional machine learning algorithms and performance metrics.
2. TensorFlow/Keras: For the development of the Deep Learning Bi-LSTM architecture.
3. Pytesseract: For the integration of Optical Character Recognition (OCR).
4. Pandas & Matplotlib: For data manipulation and results visualization.
5. OCR Engine: Tesseract (pytesseract) for extracting text from physical ingredient labels.

C. Hybrid Model Architecture

The model processes input through a multi-stage pipeline:

1. Text Extraction: Input is received through an image processed through OCR.
2. Rule-Based Lookup: The system will search for matches in the verified Knowledge Base via FOOD_ADDITIVE_LISTING_5.csv first. This ensures 100% accuracy for any known E-codes and chemical additives.
3. Predictive Analysis (Bi-LSTM): If an ingredient is not found in the database, Deep Learning model will take over.
4. Final Verdict: The system flags any ingredient identified as "Halal" or "Doubtful/Haram" by either from the database or the AI.

D. Machine Learning Algorithm and Mathematical Foundation

A core component of this research is the performance comparison between four distinct algorithms to identify the most effective predictive algorithm:

1. Logistic Regression: Used as a baseline linear model for binary classification.
2. Multinomial Naive Bayes: A probabilistic classifier effective for text-based categorization.
3. Random Forest: An ensemble learning method using 50 decision trees to handle non-linear data relationships.
4. Bidirectional LSTM (Deep Learning): A neural network with 64 units and a dropout layer (0.5)

designed to capture sequential context in ingredient lists.

The Deep Learning model uses the Binary Cross-Entropy loss function for optimization:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

Where:

- N is the number of samples.
- yi is the actual label (Halal or Doubtful/Haram).
- y^i is the predicted probability from the sigmoid activation function.

The parameters in the model include:

- Vocabulary Size: 10,000 words.
- Embedding Dimension: 64.
- Dropout Rate: 0.5 to prevent overfitting.
- Optimizer: Adam optimizer.

E. Training and Testing

1. Data Splitting: The combined dataset was split into training and testing phase (80% for training and 20% for testing), ensuring the model considered the unseen data.
2. Feature Engineering: Traditional models (Logistic Regression, Naive Bayes, Random Forest) utilize TF-IDF Vectorization with 10,000 features. The Deep Learning model uses a Tokenizer with a vocabulary size of 10,000 and a sequence padding length of 100.
3. Stratification: Stratified sampling was used during the split to maintain the balance between "Halal" and "Doubtful" classes.

F. OCR Integration Process

For real-world application, the system incorporates an image analysis function. The process involves:

1. Image loading and conversion via PIL.
2. OCR text extraction using Tesseract with a specific configuration (--oem 3 --psm 6) optimized for dense text blocks.
3. Text cleaning to remove noise and common OCR artifacts before passing the data to the classifier.

G. Performance Measurements

Four primary metrics are calculated for every model for analytical review:

- Accuracy: The overall percentage of correct predictions.
- Precision: The ability of the classifier not to label a Halal ingredient as Doubtful.
- Recall: The ability of the classifier to find all Doubtful/Haram ingredients.
- F1-Score: The harmonic mean of Precision and Recall to provide balanced metric for performance.

RESULTS

A. Sample Outputs

1) Chipster Spiral

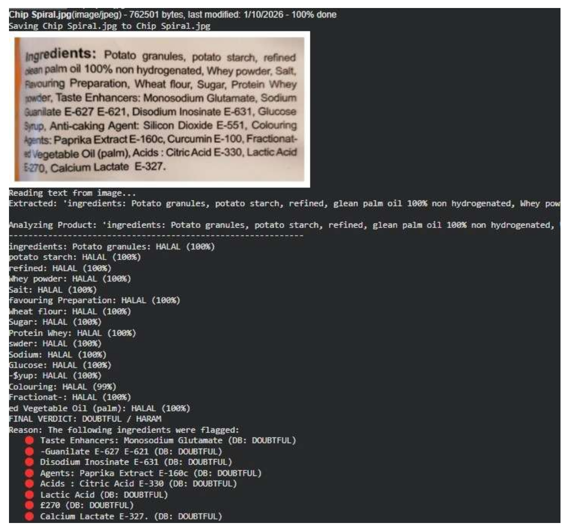


Fig 2.

2) Knorr Tomato Chatpata Soup

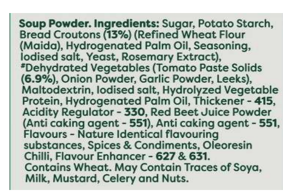


Fig 3.

B. Graphs of Bi-LSTM Model Performance

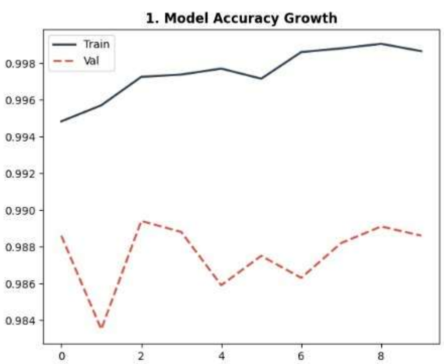


Fig 4.

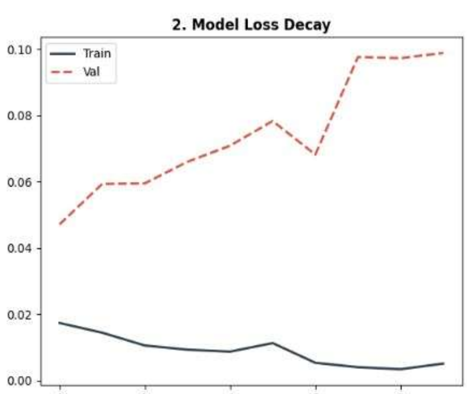


Fig 5.

Fig 6.

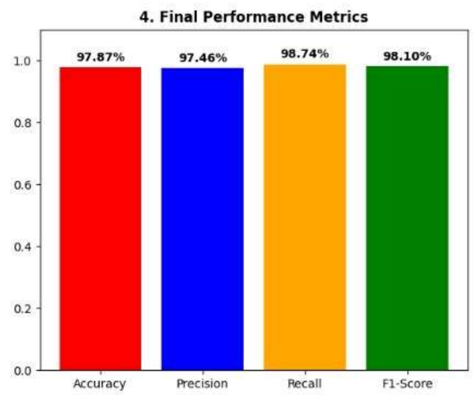


Fig 7.

C. Performance Metric Comparison

TABLE I

PERFORMANCE METRICS BETWEEN ALGORITHMS

Performance Metrics	**ALGORITHM**			
	Deep Learning	**Logistic Regression**	**Random Forest**	**Naive Bayes**
Accuracy	0.979	0.953	0.953	0.835
F1-Score	0.981	0.953	0.953	0.835
Precision	0.974	0.955	0.953	0.835
Recall	0.987	0.953	0.953	0.834

DISCUSSION AND ANALYSIS

A. Results Analysis

Fig.3 and Fig.4 shows the testing result of the Bidirectional LSTM model. The model will scan through the ingredient lists and tried to predict and label the status of each ingredient. In addition, the model will also flag all the ingredients that are potentially Haram or Doubtful/Haram. After a few tests, we verify that most of the flagged ingredients are mostly coming additives group (thickener, enhancer, regulator etc.) . The label of Doubtful is written as Doubtful/Haram as to follow the prophet S.A.W guidance originated from the Hadith:

...فَمَنْ اتَّقَى الشُّبُهَاتِ فَقْد اسْتَبْرَأَ لِدِينِهِ وَعِرْضِه

وَمَنْ وَقَعَ فِي الشُّبُهَاتِ وَقَعَ فِي الْحَرَام .....

[Bukhari & Muslim]

Translation : ... Whoever is wary of these unclear matters has absolved his religion and honor. And whoever indulges in them has indulged in the haram...

This specific labelling is following the principle of Maqasid Syariah, protection of religion. It acts as early warning to protect the consumers from supporting doubtful matter as it leans toward destruction more than the benefits could be gained.

This labelling also employed the principle of preservation of intellect because doubtful matters might contain Haram entities that are not being verified yet or known to public. As a Muslim, we must avoid consuming any doubtful matters until its status verified by trusted parties or organizations.

B. Model Performance Analysis

1) Model Accuracy Growth and Loss Decay

Fig. 4 and Fig. 5 illustrate the bidirectional LSTM's performance. Training accuracy approaches 97.9% while loss is minimized, however the validation metrics show a significant divergence and volatility. This gap justifies the presence of overfitting in our model. The model is memorizing training noise rather than extracting essential features from the sequential dataset. This is caused by the reduce dataset (50,000 samples) data that are used for training and testing.

2) Confusion Matrix

Fig. 6 illustrates the bidirectional LSTM's classification performance. The model achieves high precision, with only a moderate amount of false prediction and labelling across 10,000 samples. The matrix does demonstrate a strong class identification, although the previously noted overfitting remains a concern for broader dataset generalization.

3*) Overall Performance Metrics*

Fig. 7 illustrates the bidirectional LSTMs performs well on identifying specific group of data and predict the outcome. The high, balanced metrics reveal that the model distinguishes between classes with minimal error. However, because the results obtained is too highly accurate with 97.9% confidence, it suggests the model is overfitting. The model might struggle to label and predict when faced with real-world data it hasn't seen before.

C. Performance Metrics Comparison

Table I shows the performance comparison between algorithms along with our deep learning model. The outcome is our model, Bidirectional LSTM model is the most effective algorithm across all evaluated metrics.

The data shows that deep learning model is the top-performing model, leading with 0.979 accuracy and an 0.981 F1-score. It noticeably performs over Logistic Regression and Random Forest, which both has a lower score of 0.953 accuracy. Furthermore, the Deep Learning model is the best at predicting actual positive cases, shown by its high 0.987 recall. On the other hand, Naive Bayes struggled significantly with only 0.835 accuracy. Overall, the Deep Learning method is the most consistent and reliable choice among other algorithms as a predictive model.

D. Statistics on Muslim Consumer Behaviour

Understanding Muslim consumer behavior is critical to justifying the development and necessity of the Harmonizing the Plate System.Recent data indicates that the Halal food market is not only economically siginificant but also driven by consumers who are increasingly cautious and meticulous in their purchasing decisions,especially when official Halal certification is absent.

1) Market Size and Global Food Expenditure

According to the State of Global Islamic Economy (SGIE) Report 2024/2025, global Muslim spending on food reached USD 1.43 trillion in 2023 and is projected to grow to USD 1.94 trillion by 2028.This growth is driven not only by a Muslim population exceeding 2 billion but also by heightened awareness regarding supply chain integrity. In the tourism sector specifically,Muslim travelers are inreasingly seeking “Halal friendly” travel experiences, where the availability of assured Halal choice.These statistics demonstrate a massive market demand for technology that facilitates easier access to compliant food and products.

2) Anxiety Over Halal Status and Lack of Certification

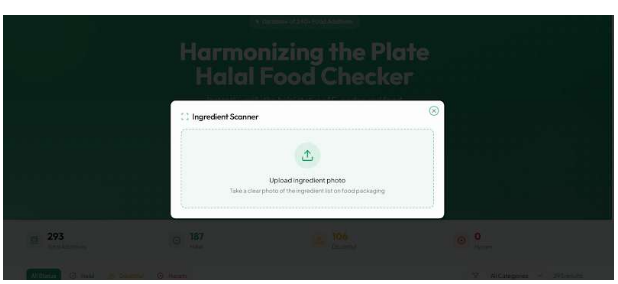
Despite market growth, Muslim consumers face significant challenges when products lack official certification. Research indicates that the absence of a Halal logo significantly impacts purchasing decisions.

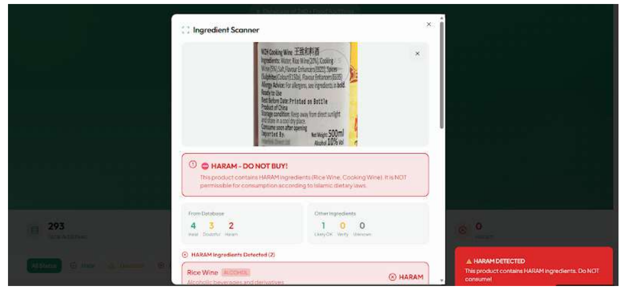
- A study conducted in Indonesia found that 88% of the Muslim population tends to avoid products without a Halal logo due to syubhah.
- Findings from Emerald Publishing (2025) highlight that the lack of universal certification standards is a major barrier in Halal tourism,causing travelers to mistrust food service providers in foreign countries.

Therefore, the integration of AI and Deep Learning in this project serves as the ideal solution to bridge the gap between the habit of reading labels and the capability to interpret those labels accurately and instantly

PROTOTYPE

A.Sample AI-Halal Food Checker Prototype





B. Prototype Limitations

1) ***Language Constraint***
The dataset used is only optimized for English corpus. The foreign languages that are fed to the model will be ignored or produce garbage results that couldn't be used for analysis.

2) ***Visual Clarity***
The quality of the picture input has a high impact on the model to read and produce results. The system struggles to detect text on crease surface or area with intense light.

3) ***INS Labeling Popularity***
Many manufacturers prefer the INS prefix because the target is on the global market rather than limited to Europe region. Furthermore, the INS Global updates more additives frequently than the E-numbering system by the European Food Safety Authority (EFSA)

FUTURE WORKS

Based on the development of the Harmonizing the Plate System and theliterature review conducted, several limitations in the current design havebeen identified.These areas present significant opportunities for future researchers to improve upon:

1. Lack of Supply Chain Provenance Verification

- Current Design Limitation: The current implementation relies entirely on Optical Character Recognition (OCR) to read products labels.This design has a critical weakness: it cannot verify the authenticity of the label itself,nor can it detect if cross-contamination occured before packaging. It trust the label implicitly
- Future Correction: Future researchers should address this by integrating Blockchain Technology.As suggested by Sunmola et al. (2024), this integration would allow the verification of Halal status based on transparent, immutable supply chain data (traceability from farm-to-fork), rather than relying solely on the physical label which is susceptible to forgery.

2. Dependency on Static Image Capture (User Experience)

- Current Design Limitation : The current workflow requires users to manually capture a static photo of a product and wait for processing.This approach is time-consuming and inefficient for tourists who wish to quickly scan multiple items on a supermarket shelf.

- Future Correction: To improve efficiency, future iterations should implement Real – Time Augmented Reality (AR).Based on the findings of Rahman et al.(2023), switching to an AR-based interface would allow users to simply point their camera at a product to see the Halal status overlain on the screen instantly, eliminationg the need for manual image capture and significantly speeding up the verification process

3. Expansion of Multilingual Support for Non-English Regions

- Current Design Limitation : The current system is primarily optimized to process lists in English.It lacks the capability to effectively interpret food labels in other foreign languages (e.g., Japanese , Korean , or Thai).This is a significant limitation for the project's target demographic, tourists who often travel to non-Muslim countries where English labels are not mandatory.

- Future Correction:Future reserarchers should address this by integrating Real-Time-Multilingual Translation capabilities.As highlighted by Tarannum (2023), incorporating translation APIs or training the AI model on a diverse, multilingual dataset is essential.This would allow the application to bridge the language barrier,ensuring the tool remains functional and useful for muslim travelers globally,regardless of the local language used on product packaging.

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