

Certainty Factor-based Expert System for Meat Classification within an Enterprise Resource Planning Framework

Adhi Kusnadi^{1,2}, Yandra Arkeman³, Khaswar Syamsu³, Sony Hartono Wijaya¹

¹ Department of Computer Science IPB University, Jl. Pajajaran, Bogor 16680, Indonesia

² Department of Informatics Universitas Multimedia Nusantara, Scientia Garden Tangerang 15111, Indonesia

³ Department of Agricultural Industrial Technology IPB University, Jl. Dramaga Bogor 16002, Indonesia

ARTICLE INFO

Article history:

Received June 14, 2023

Revised July 17, 2023

Published July 24, 2023

Keywords:

Certainty Factor (CF);

ERP;

Expert System;

Halal Beef;

Halal Products

ABSTRACT

The demand for halal products in the Islamic context continues to be high, requiring adherence to halal and haram laws in consuming food and beverages. However, individuals face the challenge of distinguishing between haram meat and permissible halal meat. This study aims to answer these challenges by designing an expert system application within the ERP framework to increase the usability functionality of the system that can differentiate between beef, pork, or a mixture of both based on the physical characteristics of the meat. The aim is to determine halal products permissible for consumption by Muslims. The research methodology includes a data collection process that involves taking 30 meat samples from various sources, and the criteria used to classify the meat will be determined based on an analysis of the physical characteristics of the meat. System administrators use expert systems to ensure proper treatment of meat during administration processes, including separating halal beef from pork and implementing different inventory procedures. The Certainty Factor (CF) inference engine deals with uncertainty even though the expert system's accuracy level is relatively good with several rules. However, these results must be studied further because the plan relies on expert opinion. Therefore, it is necessary to set the correct CF value for accurate height classification. The CF inference engine facilitates reasoned conclusions in meat classification. Functional testing confirms the smooth running of the system, validating its reliability and performance. In addition, the expert system accuracy assessment produces a commendable accuracy rate of 90%. In addition, the expert system works powerfully on various meat samples, accurately classifying meat types with high precision. This study explicitly highlights the expert system's design for meat classification in determining halal products by using the Expert System Certainty Factor. In conclusion, this expert system provides an efficient and reliable approach to classifying meat and supports the production and consumption of Halal products according to Islamic principles.

This work is licensed under a [Creative Commons Attribution-Share Alike 4.0](https://creativecommons.org/licenses/by-sa/4.0/)



Corresponding Author:

Adhi Kusnadi, Department of Computer Science IPB University, Jl. Pajajaran, Bogor 16680, Indonesia

Email: adhikusnadi@apps.ipb.ac.id

1. INTRODUCTION

Islam is the second largest religion in the world, with a population of approximately 1.9 billion out of a total global population of 7.5 billion [1]. In Islam, several laws regulate the practice of using halal and haram products, as stated in Surat Al-Baqarah verse 173 [2]. As a result, there is a high demand for these Halal products. Muslims are prohibited from consuming pork because it is considered haram in Islam [3]. However, some individuals still have difficulty distinguishing between beef (halal) and pork (haram) [4]. Due to the lack of understanding of each individual about the differences between beef, pork, or a mixture of beef and pork,

some rogue elements take advantage of this for personal gain by selling pork or a combination of pork as halal meat. This problem is very urgent, so there is a need for technology that can help humans distinguish between beef and pork. Physical differences between types of meat [5] alone cannot be considered the sole basis for determining their halal or haram status. However, this physical distinction can be a first step in identifying the type of meat, as halal compliance depends on the ingredients used and the production and storage processes involved [6]. Therefore, this research was carried out to develop an expert system within the Enterprise Resource Planning (ERP) framework that can identify the types of beef, pork, and their mixtures using an expert system so that they can distinguish between halal and haram types of meat.

Previous research studies have investigated the differences between beef and pork [7] using various approaches such as Porcine Detection Kits, antigen-antibody tests using enzyme-linked immunosorbent assay (ELISA) [8], [9], amino acid analysis [10], evaluation of the properties of odor [11], [12], and DNA examination [13]. However, this study shows certain limitations that need to be considered; first, the methods that have been used in previous studies tend to require laboratory testing, which results in limitations in terms of accessibility and affordability, in addition to the high cost associated with testing is also an obstacle in adopting these methods. This method is widely used. Second, visual identification techniques based on images of meat that have been explored [14]-[18] face challenges in accurately identifying pork mixed with beef blood which causes the accuracy level to be less than optimal [19]. Thirdly, previous research did not specifically explore the development of an expert system to differentiate beef from pork, even though expert systems have good potential in distinguishing pork, beef, or a mixture of both and can provide real-time identification advantages and provide more effective solutions [20] in determining beef and pork accurately. Therefore, this study applies an expert system that distinguishes beef, pork, or a mixture of both.

Expert systems [21], as part of Artificial Intelligence (AI) technology [22], offer many benefits and applications in various fields, such as task automation, business process efficiency, product and service quality improvement, predictive analysis, security enhancement, healthcare improvement, and education [23]-[25]. In addition, expert systems can be trained using relevant data to identify differences between pork and beef based on physical characteristics, nutritional composition, or other parameters that can assist in distinguishing beef and pork automatically and accurately. Both individuals and companies can use this system. Therefore, expert systems will be integrated into Enterprise Resource Planning (ERP) applications in this study to expand research benefits and facilitate company business process efficiency. The expert system will function as a component that interacts with the ERP to provide additional knowledge and intelligence in meat management, such as beef and pork handling, storage, and processing, to ensure meat quality and safety that complies with relevant regulations and policies. Expert systems can also assist in inventory management by grouping types of meat based on physical characteristics, nutritional composition, and others, thus enabling more efficient stock management and optimizing planning and coordination in the supply chain. By leveraging the knowledge possessed by expert systems, ERP systems can provide more comprehensive and detailed solutions in meat handling, inventory management, and supply chain processes that result in increased efficiency, accuracy, and compliance with existing policies to provide significant benefits in improving quality. Products, cost savings, and customer satisfaction.

This expert system uses the CF algorithm because it can overcome uncertainty in decision-making [26]. The certainty Factor (CF) algorithm is one of the methods used in expert systems to measure and overcome uncertainty in inferences or conclusions. This algorithm considers factors that affect the certainty of a statement or decision, such as the level of confidence or uncertainty in the input data or the rules used. The CF algorithm faces uncertainty in distinguishing beef and pork when classifying meat in this expert system. For example, some physical characteristics may provide clues, but exceptions or cases may be unclear. The CF algorithm allows the expert system to calculate confidence or certainty in conclusions based on available evidence or information. In addition, in some cases of uncertainty where some of the physical characteristics of meat may be contradictory or inconsistent, the CF algorithm can assess or consider various factors that affect the certainty of a conclusion by considering the trust or uncertainty associated with rules or input data. Thus, the CF algorithm helps the expert system to provide a level of confidence in each of the resulting conclusions so that users can understand the level of confidence in the classification results [27].

ERP offers advantages, including cost efficiency, simplified workflow, accurate and fast reporting, and integrated data analysis [28], [29]. The ERP used in this study is Odoo 15, which is open-source and integrates expert systems using Python and XML Programming Language modules. Implementation of an expert system in ERP provides additional advantages in the process of classifying and managing meat. An extensive literature review on applying ERP and AI in various domains has provided valuable insights into their synergistic potential. Notable studies include "Artificial-Intelligence-Driven Management" by M.B. Schrettenbrunner, who explores the concept of AI-Driven Management [30]; "Artificial Intelligence Applications for Optimizing

Business Processes in Enterprise Resource Planning Systems," highlighting opportunities to apply AI methods and solutions in ERP systems [31]; "Application of Lean Engineering, Enterprise Resource Planning, and Artificial Intelligence in Construction Project Management," discussing the integration of ERP and AI in Construction Project Management [32]; "Artificial Intelligence in Enterprise Resource Planning Systems: A Bibliometric Study," examines the number of publications in the field [33]; and "ERP Data Analysis and Visualization in a High-Performance Computing Environment," proposing an approach to share data in GPU memory and enhance existing ERP analytic capabilities, demonstrated using SAP S/4Hana as an example [34], [35]. These studies collectively provide a foundation for understanding the potential benefits and best practices for integrating smart contract technology within ERP frameworks and expert systems in the context of meat classification and management processes.

However, this study mainly discusses concepts, opportunities, and literature analysis without providing concrete examples of AI implementation in ERP. As a result, new and innovative topics emerged, focusing on implementing expert systems in ERP systems. This system aims to distinguish between beef, pork, or a mixture of both based on the physical characteristics of the meat. Enterprise management can take advantage of expert systems before using ERP for purchasing, inventory, accounting, and processing purposes. Administrators can handle meat efficiently by type, taking into account halal beef and its incompatibility with pork. This paper is divided into several sections, starting with an introduction to the research background. The following areas provide a brief overview of the related literature. The methods section describes the relationship between Odoo and expert systems. Implementation of the application as a prototype is presented in the fourth section, followed by a discussion in the fifth section, and conclusions in the sixth section.

There are two contributions to this research. First, it provides a new method for identifying types of pork, beef, and their mixtures using an expert system. Second, integrating two currently developing computer technologies, ERP and AI, results in a more robust system. Large-scale companies can utilize ERP, whereas AI accelerates processes by automating certain industry parts.

2. METHODS

The development of this research follows the stages of the System Development Life Cycle (SDLC) [36] (Fig. 1). At the requirements analysis stage, studies are carried out related to theories through several references in books, journals, or previous research. The design stages are not described in this manuscript due to space limitations. Each stage is completed on average within 2 months, so effectively this research is completed within 10 months.

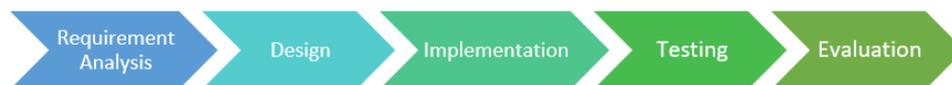


Fig. 1. System Development Life Cycle (SDLC)

In this section, the methodology used for developing and evaluating the expert system for meat type identification is based on physical characteristics. The procedure for developing and evaluating the system show in Fig. 2. The following sentence is an explanation of the Procedure for Developing and Evaluating the system:

- **Requirement Identification**
The initial stage in the research procedure is to identify the research needs. In this context, the research needs to pertain to developing an expert system for distinguishing between beef, pork, or their mixture based on the physical characteristics of the meat.
- **Technology Selection**
In the next stage, the technology selection process is carried out. For this study, the selected technology is the Certainty Factor expert system integrated with ERP by combining the ERP Odoo 15 [37] application as the central platform. This approach was chosen because integrating the certainty factor expert system provides a level of trust associated with the recommendations provided so that users can evaluate results more transparently. Integration with ERP Odoo 15 enables easy access and efficient data processing within existing environments, including inventory management and product tracking. Expert system development involves building custom Python and XML modules [38]. Python is used because it can quickly implement expert system logic and the Certainty Factor algorithm. At the same time, XML provides a structured format for defining the attributes that distinguish the types of meat. Using this approach, this research can provide a transparent, efficient, and reliable solution for identifying types of meat based on their physical characteristics.

- **Custom Module Development**
To integrate the expert system into the Odoo ERP application, modules were specially developed using Python [39] and XML programming languages [40]. This module includes the directory structure, manifest file (manifest.py), and initialization file (init.py). This module interacts with existing ERP systems by integrating the call-out of system experts into existing business processes, such as inventory management or product tracking. Through components such as the user interface, Python module, and XML data, this module allows the user to enter meat physical characteristics data and view the relief results. Therefore, this module plays a role in increasing the efficiency and accuracy of identifying the type of meat and providing a better understanding for ERP users in managing meat inventory by type.
- **Data Model Creation**
A data model is created using a model file (models.py) that defines the necessary classes and fields for meat type identification. The way to create a module for an expert system is to follow the following steps:
 - 1) Create a module directory structure with a manifest file (manifest.py) and an init file (init.py).
 - 2) Create a data model with a model file (models.py) and define the required classes and fields.
 - 3) Create views for the model with a view file (views.xml) and use XML tags to define user interface elements.
 - 4) Enable developer mode in Odoo and update the application list. Find and install the pre-built module from the Odoo user interface
- **View Creation**
Views for the model are created using a view file (views.xml) with XML tags to define user interface elements.
- **Developer Mode Activation**
Developer mode is enabled in the Odoo application, and the application list is updated. The created module is installed through the Odoo user interface.
- **Functionality Testing**
At this stage, functionality testing is carried out to ensure compliance with predetermined specifications. This study uses an expert system functionality test to identify types of meat (beef, pork, or mixed) based on their physical characteristics using 30 meat data samples with various physical features covering different cases. The process is carried out by answering several questions prepared by the system, and then the expert system will provide results based on predetermined policies.
- **Evaluation and Validation**
The results provided by the expert system are compared with the expected results. The evaluation uses accuracy metrics to measure the extent to which the expert system can provide correct predictions by calculating the actual number of predictions with the total number of cases evaluated. Validation can also involve domain experts in the same field as the tested expert system. By going through the testing and validation stages described above, a proficient expert system can be developed that offers recommendations or solutions that are appropriate and relevant to the existing conditions.

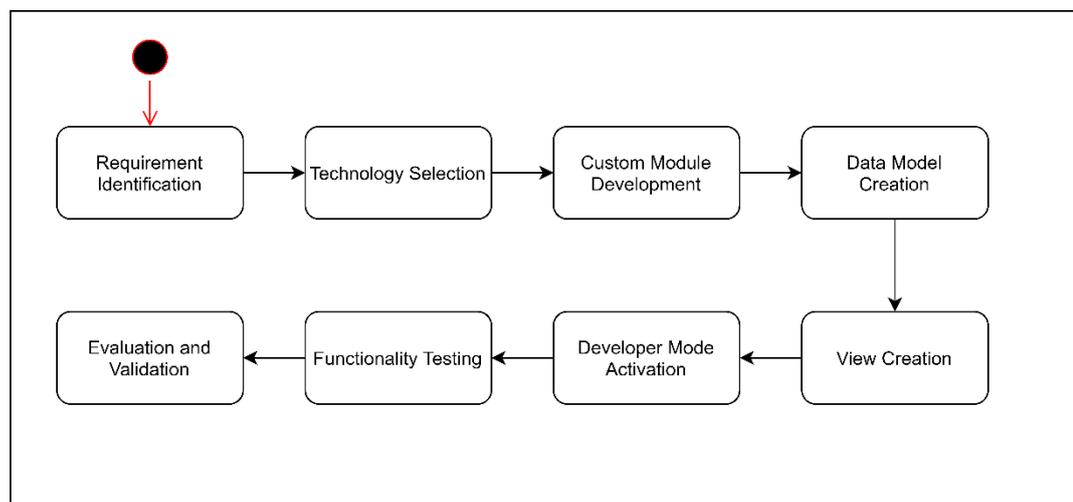


Fig. 2. The Procedure for Developing and Evaluating the System

3. RESULTS AND DISCUSSION

3.1. Result

3.1.1. Odoo

An expert system built in Odoo ERP using a particular module created in Visual Studio has been successfully implemented. The implementation involves developing custom modules with Python and XML, integrating modules into the Odoo ERP structure, and managing interactions with the ERP system. This custom module plays an essential role in accurately identifying the type of meat based on its physical characteristics. In integrating modules into Odoo ERP, the first step is to create a module directory structure with a manifest file (`manifest.py`) and an init file (`init.py`). Then, this custom module introduces a data model using the model file (`models.py`) to define the required classes and attributes. Additionally, view files (`views.xml`) are used to create views and user interfaces using appropriate XML tags.

These custom modules interact with the Odoo ERP system by leveraging existing functionality, such as inventory management or product tracking. In identifying the type of meat, the custom module processes the input data, applies the logic of the Certainty Factor expert system, and generates recommendations based on the confidence level. The identification results are then integrated into existing business processes in the ERP, such as inventory management or product tracking, based on the type of meat identified. Modules can also provide transparent visual displays or reports to make it easier for ERP users to view and analyze data related to the kinds of meat available. Thus, by integrating custom modules created in Visual Studio into the Odoo ERP platform, the expert system was successfully implemented to accurately identify the type of meat based on its physical characteristics. The module's interaction with the ERP system allows users to manage better and understand meat inventory, while the module's functionality optimizes efficiency and accuracy in the meat type identification process. In this section, we present the results and comprehensively discuss the research findings. The expert system built on Odoo ERP using a custom module created in Visual Studio [41] was successfully implemented. Fig. 3 illustrates the display of the XML coding results in the form, which requires inputting meat characteristics and CF values based on Table 2.

Fig. 3. View of Odoo XML Custom Forms

An example of the results obtained is shown in Fig. 4. The name column is a title or label that functions as a marker that helps users understand the purpose of the form being filled out. The question column of the form has a function to present questions to the user related to the identification of types of meat based on their physical characteristics; as many as 15 questions need to be answered to determine the type of meat to be consulted, answering these questions also serves as a function test of the functionality of the expert system implemented in Odoo. CF1 and CF2 stand for Certainty Factor 1 and Certainty Factor 2. The certainty Factor is used in expert systems to measure the level of confidence or certainty related to recommendations or solutions provided by the system. CF1 and CF2 values range from -1 to 1. Positive values indicate a higher confidence level in a particular suggestion, while negative values indicate a lower one. CF1 and CF2 are usually generated from an expert system inference process, in which the system evaluates existing information and rules to produce recommendations based on the physical characteristics of the observed meat. In the figure given, the values of CF1 and CF2 have different values for different questions. This shows that the expert system gives different weights to the questions and various physical characteristics in identifying the type of meat. In the example, the numbers show that the expert system provides more confidence to recommend that

the meat is beef based on dark red or blood red physical characteristics. In contrast, the expert system gives higher confidence in recommending that the meat is pork based on the physical characteristics of pink or looks pale. The test results show that the system operates smoothly, accurately identifying the type of meat.

| Name | | | |
|---|-------|-------|----|
| Beef or Pork Based on Characteristics | | | |
| Question | CF 1 | CF 2 | |
| 1. Is the color of meat dark red or blood red | 0.80 | -0.10 | 🗑️ |
| 2. Is the color of meat pink or looks pale | -0.80 | 0.80 | 🗑️ |

Fig. 4. View of Custom Form after it is filled

3.1.2. Expert System

Expert System [42] has two environments; the consultation environment is used by users who will carry out identification [43]. This environment displays a user interface that allows users to enter data on the physical characteristics of meat and get recommendations for identifying types of meat based on predetermined rules. The second environment is the development environment used by knowledge engineers in translating expert knowledge into rules in this study implemented in Odoo custom modules. This environment facilitates organizing and organizing expert knowledge into a format that expert systems can understand and implement. The calculation begins by selecting the characteristics of the meat, then the CF value. The calculation process is carried out until all CF values [44] of the selected feature facts are calculated. The main components of the expert system in this study include the following processes:

- Data Acquisition

The main methods of knowledge acquisition are interviews and literature studies [45]. Interviews were conducted with 2 experts namely Prof. Khaswar Syamsu as an expert staff at the Indonesian Ulama Council (MUI) and Prof. Retno Widyani, a Professor of Animal Husbandry. Prior to the interview, a literature study was carried out to prepare questions before face-to-face meetings. Table 1 shows the difference between beef and pork, according to a meat expert at the Department of Food Science and Technology, Bogor Agricultural University, Prof. Dr. Ir. Joko Hermianto [46].

Table 1. Differences between Beef and Pork

| No | Features | Beef | Pork |
|----|----------|--|--|
| 1 | Color | Cherry red and bright | The pink color to dark red |
| 2 | Flesh | Meat fibers are relatively coarse | Meat fiber is relatively bigger than meat goat |
| 3 | Smell | The smell does not deviate (no smells of fishy, pungent, and sour) | Stench |

- Knowledge Base

Rule reasoning is done at this stage, where knowledge is represented using IF-THEN rules. IF-THEN rules are used to represent knowledge in the form of logical rules. Each rule consists of condition (IF) and action (THEN). Conditions contain statements that must be met or fulfilled, while actions contain consequences or recommendations that will be taken if the conditions are met. By applying IF-THEN rules, expert systems can decide based on existing conditions. The following is a table consisting of 15 characteristics with conditions that must be carried out before identification:

Based on expert opinion, CF rules and values are presented in Table 2. Experts provide a scale of weight values for each symptom between -1 to 1. Then a rule is created to deduce the type of meat: IF Color AND Fiber AND Fat AND Texture AND Aroma, Then the Type of Meat. Users are given a choice of answers with CF values shown in Table 3.

- Inference Machine

CF can be applied to premises (facts) and rules [47]. The premises are the available facts, while the rules are the hypotheses given by the experts. If CF is applied to the belief, the CF value on the premise represents the degree of confidence in the facts. If CF is used as a rule, then the CF value denotes the degree of confirmation of a hypothesis. As should be the law of probability, the lower limit of the CF value is -1 (pork), meaning that the facts contradict the hypothesis, while the upper limit of the CF value is 1 (beef), meaning that the facts strongly support the hypothesis. Mathematically, the combination of the certainty factor (CF) formulation that can be used according to Turban [34] is where the rule with

more than one conclusion and more than one symptom and uses conjunction rules such as IF E1 AND E2 AND En THEN H, then the result what you are looking for is the CF combination first. Combination CF initially calculates 2 CFs first, then the CF results are calculated again with the next CF until all CFs have been estimated. Based on the CF value, the combined CF is calculated by the equation in 1 or 2, or 3 (Fig. 2). CF combination formula show in Fig. 5.

Table 2. Characteristics of Meat and Weighting CF

| No | Features | Characteristic | CF Score | |
|----|----------|---|----------|------|
| | | | Beef | Pork |
| 1 | Color | Dark red or blood red | 0.8 | -0.1 |
| 2 | | Pink or pale | -0.8 | 0.8 |
| 3 | | Like chicken | -0.8 | 0.8 |
| 4 | Fiber | Looks solid, many or clear | 0.6 | -0.8 |
| 5 | | Looks distant, little or faint | -0.4 | 0.6 |
| 6 | | Looks lean | -0.4 | 0.5 |
| 7 | Fat | Look stiff, dry, easily detached, and lumpy | 0.8 | -0.8 |
| 8 | | Looks elastic, wet, difficult to remove and clump | -0.8 | 0.6 |
| 9 | Texture | Looks involved | -0.8 | 0.8 |
| 10 | | Solid, hard, and hard to stretch | 0.6 | -0.6 |
| 11 | | Rigid | 0.6 | -0.5 |
| 12 | Smell | It's springy, mushy, and stretches easily | -0.4 | 0.8 |
| 13 | | Blood rancid and thick rancid | 0.4 | -0.6 |
| 14 | | Typical and fishy | -0.4 | 0.4 |
| 15 | | Strong stench | -0.4 | 0.4 |

Table 3. User Answer Value

| No | Answer | CF Score |
|----|-----------------|----------|
| 1 | Dont know | 0.0 |
| 2 | Not sure | 0.2 |
| 3 | Not yet sure | 0.4 |
| 4 | Quiet Confident | 0.6 |
| 5 | Confident | 0.8 |
| 6 | Very Confident | 1 |

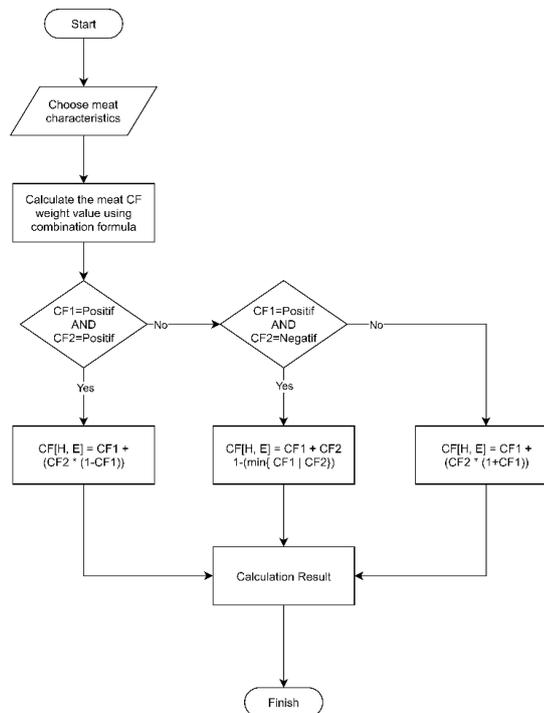


Fig. 5. CF Combination Formula

| | |
|-----------|--|
| CF1 | = CF value of symptom 1 or first CF value |
| CF2 | = CF value of symptom 2 or second CF value |
| CF [H, E] | = CF value of the combination of existing symptoms |

- Expert System Testing

The expert system validation testing achieved an impressive accuracy rate of 90%. 30 system tests were conducted using meat samples with known type labels, where the correct answers matched expert opinions and meat labels in 27 cases.

3.1.3. Discussion

Expert system test results show relatively good accuracy for expert systems, even with a limited number of rules. However, expert opinion and engineering know-how are still needed to build an intelligent system that determines the appropriate parameters and identification criteria and validates the compatibility and accuracy of system results. In this context, experts and knowledge engineers focus on designing and organizing the knowledge needed for intelligent systems. They are responsible for interpreting the butcher's knowledge and translating it into the necessary rules and logic. Therefore, human involvement is still necessary to ensure the accuracy and relevance of the knowledge and interpretation that underlies it. In addition, it is essential to consider potential drawbacks. Additional costs may be incurred, especially if the company needs to acquire the necessary knowledge or skills to develop software. The system's dependence on expert expertise is another challenge, as experts with sufficient knowledge in the relevant field must construct an expert system knowledge base. Maintaining and repairing systems presents an ongoing challenge to ensure consistent and accurate results. When comparing the advantages and disadvantages depending on the specific needs and requirements of the organization to implement an expert system in ERP, the application should be adjusted according to the organization's level of needs and capacity. Proper implementation of AI in ERP can generate significant benefits, as supported by previous studies [48], [49]. However, carefully assessing business needs, objectives, and capabilities to integrate and effectively utilize technology is necessary to mitigate potential losses and negative impacts on business.

This study takes a different approach from previous research entitled "Classification of pork and beef images using color and texture feature extraction using the Gray Level Co-Occurrence Matrix method" [50]. Previous research focused on the classification of beef and pork using digital analysis. Imagery and Back-propagation method with an accuracy of up to 89.57%. This research focuses on developing an expert system that can distinguish between beef, pork, and their mixtures based on the physical characteristics of the meat using the Certainty Factor expert system. Although the difference in accuracy between this study and previous research may seem insignificant, it is essential to consider the broader context of technological advances and research contributions. In the meat identification field, even minor accuracy improvements can have significant implications for various industries, such as food processing, quality control, and consumer protection.

In addition, the novelty of this study is based not solely on achieving a slightly higher level of accuracy but on developing an expert system that utilizes the Certainty Factor Formula inference engine to identify types of meat based on physical characteristics. This approach offers an alternative, more efficient solution than the image analysis-based methods used in previous studies. The significance of technological advances in this study lies in their contribution to the field of expert systems and the integration of these systems into the Odoo ERP platform. By providing a reliable and automated method for differentiating beef, pork, and their blends, this research offers practical benefits to industry and consumers, including better decision-making, product quality control, and cost savings. Therefore, even though the difference in accuracy may not be significant, the use of the Certainty Factor expert system based on the physical characteristics of meat can be an effective alternative in identifying types of meat and making a valuable contribution to the development of technology and improving the quality of related industries.

However, expert systems have potential limitations that need to be considered. One of them is the dependence on expert expertise. Expert systems require the knowledge and expertise of human experts to build the system's knowledge base. This means that expert systems depend highly on the availability of experts with sufficient knowledge in the relevant field. In addition, even though expert systems can produce accurate results, it still requires human involvement to ensure the accuracy and relevance of the underlying knowledge. Humans need to be involved in validating the compatibility and accuracy of system results and ensuring proper interpretation of knowledge. In addition, expert systems also have a limited number of rules. An expert system may only be able to cover some possible complex situations or cases, affecting its ability to provide solutions in situations that have not been regulated or covered in its knowledge base. In addition, developing expert systems can also incur additional costs, especially if a company needs to acquire the knowledge or skills needed

to develop software. Costs of expert training, data collection, and development of suitable infrastructure may be incurred. Maintenance and repair of expert systems is also an ongoing challenge. Periodic updates and adjustments are required to keep the system consistent and accurate. In this context, human involvement and expert expertise remain essential factors in building and maintaining expert systems. Despite its limitations, the proper implementation of an expert system in ERP can provide significant benefits in decision-making, quality control, and cost savings.

4. CONCLUSION

In conclusion, this study achieved its goal of overcoming the challenges of identifying meat by designing and building an expert system application within an Enterprise Resource Planning (ERP) framework. These challenges include the complexity of differentiating types of meat based on their physical characteristics, such as similarities in the physical characteristics of meat, the presence of a mixture of various types of meat, and human subjectivity in assessing the physical characteristics of meat. The findings of the "Results and Discussion" chapter have provided valuable insights into developing an expert system to identify beef, pork, and their blends based on physical characteristics. The results show the system's effectiveness in achieving an accuracy rate of 90% in differentiating types of meat. This level of accuracy reflects the system's effectiveness in distinguishing types of meat based on their physical characteristics, such as color, texture, and aroma. These results validate the feasibility and potential of utilizing a combination of physical characteristics and the Certainty Factor Combination Formula as an inference engine for identifying meat types. Existing methods and industry standards can guide system performance evaluation in the meat identification industry. Future research expansion can broaden the analysis and comparison with existing methods and industry standards to provide a more comprehensive assessment of the performance of the expert system developed in this study. By comparing the level of accuracy of the expert system with existing methods or industry standards, it can be understood to what extent this expert system is reliable in meat identification practices. In addition, the potential impact of expert systems on meat identification practices also needs to be explored further. Research results showing a high accuracy level provide practical benefits for industry and consumers. With better decision-making capabilities, better product quality control, and cost savings, expert systems can be valuable tools in increasing efficiency and reliability in meat identification.

Thus, the research results hold promise for future development and advancement of this field. These findings may serve as a foundation to inspire further studies in the meat species identification domain, with potential areas to be explored. One area that could be explored is expanding the expert system's knowledge base by collecting additional data on the physical characteristics of meat species that could help improve the expert system's ability to identify various types of meat more accurately and reliably. In addition, integrating advanced technologies such as machine learning and computer vision can enhance the capabilities of expert systems, opening new avenues for research and innovation. The use of machine learning methods, such as classification algorithms and pattern recognition, allows expert systems to learn from the collected data and build models that can identify complex patterns to increase the system's ability to distinguish the physical characteristics of meat accurately. However, using this method has several limitations that need to be considered; one of the limitations is the reliance on representative training data. Suppose the training data needs to cover a sufficient variety of meat types to be identified. In that case, the expert system may need help recognizing rare meat types or not represented in the training data. In addition, interpreting results from machine learning models can also be challenging, especially if the model is complex and difficult to explain intuitively.

These advances could revolutionize the meat identification field, offering practical benefits to industry and consumers, including better decision-making, better product quality control, and cost savings. The research results validate the initial expectations set out in the "Introduction" chapter and provide a solid basis for developing and expanding future research in this area. The fit between the expected and the results obtained reinforces the importance of this research and its potential impact on various industries. The findings inspire further studies, encouraging researchers to explore new possibilities and advances in meat identification, benefiting both industry and consumers.

Acknowledgments

Thank you to IPB University and Universitas Multimedia Nusantara for providing research facilities. Thanks also to Yosia Heartha Dhalasta Wangsajaya, an Informatics student at Universitas Multimedia Nusantara, who assisted with this research. And thanks to Mr. Mutahik as an expert who provided his knowledge and tested this expert system application.

REFERENCES

- [1] A. Kusnadi, Y. Arkeman, K. Syamsu, and S. H. Wijaya, "Designing Halal Product Traceability System using UML and Integration of Blockchain with ERP," *Register: Jurnal Ilmiah Teknologi Sistem Informasi*, vol. 9.1, pp. 29–41, 2023, <https://doi.org/10.26594/register.v9i1.3045>.
- [2] E. H. Purwanto, B. D. Tampubolon, W. C. Anggundari, A. Dewantoro, P. Anggraeni, and U. Ayuningtyas, "Potential technical parameters for the authentication of carrion meat (tiren): A review," *Int Food Res J*, vol. 30, no. 1, pp. 46–62, 2023, <https://doi.org/10.47836/ifrj.30.1.03>.
- [3] O. B. Amao, "A decade of terror: revisiting Nigeria's interminable Boko Haram insurgency," *Security Journal*, vol. 33, no. 3, pp. 357–375, 2020, <https://doi.org/10.1057/s41284-020-00232-8>.
- [4] B. A. Altmann *et al.*, "Human perception of color differences using computer vision system measurements of raw pork loin," *Meat Sci*, vol. 188, p. 108766, 2022, <https://doi.org/10.1016/j.meatsci.2022.108766>.
- [5] S. Martini, A. Conte, and D. Tagliacruzchi, "Comparative peptidomic profile and bioactivities of cooked beef, pork, chicken and turkey meat after in vitro gastro-intestinal digestion," *J Proteomics*, vol. 208, p. 103500, 2019, <https://doi.org/10.1016/j.jprot.2019.103500>.
- [6] M. Tieman, M. R. Darun, Y. Fernando, and A. B. Ngah, "Utilizing Blockchain Technology to Enhance Halal Integrity: The Perspectives of Halal Certification Bodies," *Services-SERVICES 2019: 15th World Congress, Held as Part of the Services Conference Federation*, pp. 119–128, 2019 https://doi.org/10.1007/978-3-030-23381-5_9.
- [7] B. Leuret and M. Čandek-Potokar, "Review: Pork quality attributes from farm to fork. Part II. Processed pork products," *Animal*, vol. 16, p. 100383, 2022, <https://doi.org/10.1016/j.animal.2021.100383>.
- [8] B. Kuswandi, A. A. Gani, and M. Ahmad, "Immuno strip test for detection of pork adulteration in cooked meatballs," *Food Biosci*, vol. 19, pp. 1–6, 2017, <https://doi.org/10.1016/j.fbio.2017.05.001>.
- [9] L. Asensio, I. González, T. García, and R. Martín, "Determination of food authenticity by enzyme-linked immunosorbent assay (ELISA)," *Food Control*, vol. 19, no. 1, pp. 1–8, 2008, <https://doi.org/10.1016/j.foodcont.2007.02.010>.
- [10] Ramin Jorfi, "Differentiation of pork from beef, chicken, mutton and chevon according to their primary amino acids content for halal authentication," *Afr J Biotechnol*, vol. 11, no. 32, 2012, <https://doi.org/10.5897/AJB11.3777>.
- [11] M. Nurjuliana, Y. B. Che Man, D. Mat Hashim, and A. K. S. Mohamed, "Rapid identification of pork for halal authentication using the electronic nose and gas chromatography mass spectrometer with headspace analyzer," *Meat Sci*, vol. 88, no. 4, pp. 638–644, 2011, <https://doi.org/10.1016/j.meatsci.2011.02.022>.
- [12] R. Sarno, K. Triyana, S. I. Sabilla, D. R. Wijaya, D. Sunaryono, and C. Fatichah, "Detecting Pork Adulteration in Beef for Halal Authentication Using an Optimized Electronic Nose System," *IEEE Access*, vol. 8, pp. 221700–221711, 2020, <https://doi.org/10.1109/ACCESS.2020.3043394>.
- [13] A. F. El Sheikha, N. F. K. Mokhtar, C. Amic, D. U. Lamasudin, N. M. Isa, and S. Mustafa, "Authentication technologies using DNA-based approaches for meats and halal meats determination," *Food Biotechnol*, vol. 31, no. 4, pp. 281–315, 2017, <https://doi.org/10.1080/08905436.2017.1369886>.
- [14] A. Elfakharany, R. Yusof, N. Ismail, R. Arfa, and M. Yunus, "Halalnet: a deep neural network that classifies the halalness slaughtered chicken from their images," *arXiv preprint arXiv:1906.11893*, 2019, <https://doi.org/10.48550/arXiv.1906.11893>.
- [15] L. V Utkin, M. S. Kovalev, and E. M. Kasimov, "An explanation method for Siamese neural networks," *Proceedings of International Scientific Conference on Telecommunications, Computing and Control*, pp. 219–230, 2021, https://doi.org/10.1007/978-981-33-6632-9_19.
- [16] L. Handayani *et al.*, "Comparison of target probabilistic neural network (pnn) classification for beef and pork," *J Theor Appl Inf Technol*, vol. 30, no. 12, 2017, http://repository.uin-suska.ac.id/70554/2/JATIT_BuktiKorespondensi.pdf.
- [17] M. Tan and Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," *International conference on machine learning*, pp. 6105–6114, 2019, <http://proceedings.mlr.press/v97/tan19a.html?ref=jina-ai-gmbh.ghost.io>.
- [18] H. T. Gorji *et al.*, "Combining deep learning and fluorescence imaging to automatically identify fecal contamination on meat carcasses," *Sci Rep*, vol. 12, no. 1, p. 2392, 2022, <https://doi.org/10.1038/s41598-022-06379-1>.
- [19] R. Sarno, K. Triyana, S. I. Sabilla, D. R. Wijaya, D. Sunaryono, and C. Fatichah, "Detecting Pork Adulteration in Beef for Halal Authentication Using an Optimized Electronic Nose System," *IEEE Access*, vol. 8, pp. 221700–221711, 2020, <https://doi.org/10.1109/ACCESS.2020.3043394>.
- [20] B. A. Aly, T. Low, D. Long, C. Baillie, and P. Brett, "Robotics and sensing technologies in red meat processing: A review," *Trends Food Sci Technol*, vol. 137, pp. 142–155, 2023, <https://doi.org/10.1016/j.tifs.2023.05.015>.
- [21] B. Raharja, E. B. Samudera, F. Lay, and S. Hansun, "Expert system for depression detection in teenagers," *System research and information technologies*, no. 2, pp. 143–150, 2022, <https://doi.org/10.20535/SRIT.2308-8893.2022.2.12>.
- [22] A. Asemi, A. Ko, and M. Nowkarizi, "Intelligent libraries: a review on expert systems, artificial intelligence, and robot," *Library Hi Tech*, vol. 39, no. 2, pp. 412–434, 2021, <https://doi.org/10.1108/LHT-02-2020-0038>.
- [23] T. H. Davenport, and R. Ronanki, "Artificial intelligence for the real world," *Harvard business review*, vol. 96, no. 1, pp. 108–116, 2018, <https://blockqai.com/wp-content/uploads/2021/01/analytics-hbr-ai-for-the-real-world.pdf>.
- [24] A. Agrawal, J. S. Gans, and A. Goldfarb, "Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction," *Journal of Economic Perspectives*, vol. 33, no. 2, pp. 31–50, 2019, <https://doi.org/10.1257/jep.33.2.31>.

- [25] A. Sathish and T. Dhanabalan, "Transforming Indian industries through artificial intelligence and robotics in industry 4.0," *International Journal of Mechanical Engineering and Technology (IJMET)*, vol. 9, no. 10, pp. 835–845, 2018, https://iaeme.com/MasterAdmin/Journal_uploads/IJMET/VOLUME_9_ISSUE_10/IJMET_09_10_087.pdf.
- [26] R. M. Zulqarnain *et al.*, "Algorithms for a Generalized Multipolar Neutrosophic Soft Set with Information Measures to Solve Medical Diagnoses and Decision-Making Problems," *Journal of Mathematics*, vol. 2021, pp. 1–30, 2021, <https://doi.org/10.1155/2021/6654657>.
- [27] T. R. Chhetri, A. Hohenegger, A. Fensel, M. A. Kasali, and A. A. Adekunle, "Toward improving prediction accuracy and user-level explainability using deep learning and knowledge graphs: A study on cassava disease," *Expert Syst Appl*, p. 120955, 2023, <https://doi.org/10.1016/j.eswa.2023.120955>.
- [28] G. A. Langenwalter, *Enterprise Resources Planning and Beyond*. CRC Press, 2020, <https://doi.org/10.1201/9781420049060>.
- [29] Y. Wang, L. Kung, and T. A. Byrd, "Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations," *Technol Forecast Soc Change*, vol. 126, pp. 3–13, 2018, <https://doi.org/10.1016/j.techfore.2015.12.019>.
- [30] M. B. Schrettenbrunner, "Artificial-Intelligence-Driven Management," *IEEE Engineering Management Review*, vol. 48, no. 2, pp. 15–19, 2020, <https://doi.org/10.1109/EMR.2020.2990933>.
- [31] K. Anguelov, "Applications of Artificial Intelligence for Optimization of Business Processes in Enterprise Resource Planning Systems," in *2021 12th National Conference with International Participation (ELECTRONICA)*, pp. 1–4, 2021, <https://doi.org/10.1109/ELECTRONICA52725.2021.9513677>.
- [32] A. Bulgakov and T. Bock, "Integration of Lean Management Methods in Construction and the Building Information Modelling," *MATEC Web of Conferences*, vol. 251, p. 05040, 2018, <https://doi.org/10.1051/mateconf/201825105040>.
- [33] C. Aktürk, "Artificial Intelligence in Enterprise Resource Planning Systems: A Bibliometric Study," *Journal of International Logistics and Trade*, vol. 19, no. 2, pp. 69–82, 2021, <https://doi.org/10.24006/jilt.2021.19.2.069>.
- [34] A. N. Sisuykov, V. K. Bondarev, and O. S. Yulmetova, "ERP Data Analysis and Visualization in High-Performance Computing Environment," in *2020 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus)*, pp. 509–512, 2020, <https://doi.org/10.1109/EIConRus49466.2020.9038949>.
- [35] Y. T. Prasetyo and K. O. S. Soliman, "Usability Evaluation of ERP Systems: A Comparison between SAP S/4 Hana & Oracle Cloud," in *2021 IEEE 8th International Conference on Industrial Engineering and Applications (ICIEA)*, pp. 120–125, 2021, <https://doi.org/10.1109/ICIEA52957.2021.9436697>.
- [36] C. Wallin, "Software Development Lifecycle Models The Basic Types," *Research Methodology for Computer Science and Engineering*, 2001.
- [37] B. Arifianto, S. S. Azhar, D. F. Murad, and W. J. Widjaja S, "Evaluation and Recommendation of Odoo Enterprise Resource Planning System Operation & Maintenance Module," in *2023 8th International Conference on Business and Industrial Research (ICBIR)*, pp. 102–107, 2023, <https://doi.org/10.1109/ICBIR57571.2023.10147555>.
- [38] H. K. Dhalla, "A Performance Analysis of Native JSON Parsers in Java, Python, MS.NET Core, JavaScript, and PHP," in *2020 16th International Conference on Network and Service Management (CNSM)*, pp. 1–5, 2020, <https://doi.org/10.23919/CNSM50824.2020.9269101>.
- [39] A. Nagpal and G. Gabrani, "Python for Data Analytics, Scientific and Technical Applications," in *2019 Amity International Conference on Artificial Intelligence (AICAI)*, pp. 140–145, 2019, <https://doi.org/10.1109/AICAI.2019.8701341>.
- [40] N. Al Madi, D. Guarnera, B. Sharif, and J. Maletic, "EMIP Toolkit: A Python Library for Customized Post-processing of the Eye Movements in Programming Dataset," in *ACM Symposium on Eye Tracking Research and Applications*, pp. 1–6, 2021, <https://doi.org/10.1145/3448018.3457425>.
- [41] A. Del Sole, *Visual Studio Code Distilled*. Berkeley, CA: Apress, 2021, <https://doi.org/10.1007/978-1-4842-6901-5>.
- [42] D. Sabin and C. Peltier, "Utilization of an Expert System Enhanced with Machine Learning for Automatic Voltage Sag Identification and Analysis," in *2022 20th International Conference on Harmonics & Quality of Power (ICHQP)*, pp. 1–5, 2022, <https://doi.org/10.1109/ICHQP53011.2022.9808700>.
- [43] H. Souabni, H. Benbrahim, and A. Amine, "Secure Data Acces in Odoo System," in *2022 8th International Conference on Optimization and Applications (ICOA)*, pp. 1–5, 2022, <https://doi.org/10.1109/ICOA55659.2022.9934479>.
- [44] A. Azareh *et al.*, "Modelling gully-erosion susceptibility in a semi-arid region, Iran: Investigation of applicability of certainty factor and maximum entropy models," *Science of the Total Environment*, vol. 655, pp. 684–696, 2019, <https://doi.org/10.1016/j.scitotenv.2018.11.235>.
- [45] A. Riyadi, "Design of Backward Chaining for Identification Palm Oil Diseases Base on Expert System," in *Journal of Physics: Conference Series*, p. 12112, 2021, <https://doi.org/10.1088/1742-6596/1823/1/012112>.
- [46] J. Hermanto, "Mengenal Beda Daging Sapi & Daging Babi – Seafast Center," *IPB University*, 2019. <http://seafast.ipb.ac.id/mengenal-beda-daging-sapi-daging-babi/> (accessed Oct. 22, 2021).
- [47] A. L. Prasasti, I. A. Rahmi, S. F. Nurahmani, and A. Dinimaharawati, "Mental Health Helper: Intelligent Mobile Apps in the Pandemic Era," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI)*, vol. 7, no. 3, pp. 479–490, 2021, <http://dx.doi.org/10.26555/jiteki.v7i3.22012>.
- [48] R. Chopra, L. Sawant, D. Kodi, and R. Terkar, "Utilization of ERP systems in manufacturing industry for productivity improvement," *Mater Today Proc*, vol. 62, pp. 1238–1245, 2022, <https://doi.org/10.1016/j.matpr.2022.04.529>.
- [49] N. Yathiraju, "Investigating the use of an Artificial Intelligence Model in an ERP Cloud-Based System," *International Journal of Electrical, Electronics and Computers*, vol. 7, no. 2, pp. 1–26, 2022, <https://doi.org/10.22161/eec.72.1>.

- [50] R. A. Asmara *et al.*, "Classification of pork and beef meat images using extraction of color and texture feature by Grey Level Co-Occurrence Matrix method," *IOP Conf Ser Mater Sci Eng*, vol. 434, p. 012072, 2018, <https://doi.org/10.1088/1757-899X/434/1/012072>.

BIOGRAPHY OF AUTHORS



Adhi Kusnadi, Doctor candidate from IPB University, Lecture at Universitas Multimedia Nusantara. Email : adhikusnadi@apps.ipb.ac.id, ORCID ID 0000-0002-4446-5526.



Yandra Arkeman, Professor in Agroindustrial Technology with research interests in Computational Intelligence and Advanced Computing Technology. Email: yandra@apps.ipb.ac.id . ORCID 0000-0002-6183-6069.



Khaswar Syamsu, Professor of Bioprocess Engineering, Department of Agricultural Technology, FATETA IPB University. Email : iwanks@apps.ipb.ac.id, ORCID ID 0000-0002-5113-8830.



Sony Hartono Wijaya, Doctor with expertise in Bioinformatics, Machine Learning, Information Retrieval, Software Engineering, and Mobile Apps Development with many programming languages and Head of the IPB University Computer Science department. Email : sony@apps.ipb.ac.id. ORCID ID 0000-0002-4603-6928.