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# Expert system for diagnosing EDC cash register malfunctions using the Decision Tree method

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**ABSTRACT**

Problems with the use of Electronic Data Capture (EDC) machines at Jinjja Chicken Center Point Medan restaurant pose a significant challenge, especially since EDC machines not only function as a means of cashless payment, but also as part of the cashier's operational system. Frequent disruptions include program errors, display errors, total EDC shutdowns, line idles, and "please try again" messages. Until now, the process of reporting and repairing EDC malfunctions has been done manually by submitting a request to the bank, which often makes the diagnosis and repair process slow and inefficient. This is exacerbated by the limited technical information available to restaurant operators when customers experience disruptions. To overcome these problems, this study aims to develop an expert system for diagnosing EDC cash register malfunctions using the Decision Tree method, which is capable of mimicking the way an expert diagnoses EDC problems quickly and accurately. The Decision Tree method was chosen because it is capable of mapping the decision-making process based on attributes or symptoms that arise, to produce a conclusion in the form of the type of malfunction. This system was built using the PHP programming language and run locally using XAMPP as a web server. The research was conducted in a limited setting at the Jinjja Chicken Center Point restaurant in Medan, with five main malfunction categories as variables: Program Error, Display Error, EDC Completely Dead, Line Idle, and Please Try Again. The final result of this system development is expected to provide practical, efficient solutions that approximate the capabilities of an expert, as well as make a real contribution to the utilization of expert system technology to assist in the diagnosis of digital device damage in the service sector.



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## Introduction

The development of digital technology has brought significant transformations to global payment systems, including in the retail and food service sectors (Korobeynikova, 2021; Voytovych et al., 2020). One technology that plays an important role in supporting cashless transactions is Electronic Data Capture (EDC), which not only functions as a means of payment using debit and credit cards, but also as a vital instrument in supporting business operations (Aorora, 2022; Fadhilah et al., 2023). The reliability of EDC machines is a crucial factor in maintaining smooth transactions, especially in the restaurant industry, which has a high transaction intensity and prioritizes service efficiency. However, the use of EDC machines is not without various technical problems, such as application installation errors, human error, hardware damage, and electrical short circuits. These problems often disrupt the payment process, which ultimately affects customer satisfaction and the operational efficiency of the company. In practice, the process of handling EDC machine malfunctions generally still depends on banks or service providers, where restaurant owners or managers must submit damage reports and wait for a response from technicians (Hesananda et al., 2024). This dependence on manual processes causes delays, especially considering the large number of EDC devices spread across various locations, meaning that technicians cannot always respond quickly (Fernaldo & Sani, 2023). This condition highlights the need for an alternative approach that is capable of independently diagnosing malfunctions before technician intervention. One solution that can be offered is the development of an expert system, which is a computer-based system that adopts the knowledge and experience of an expert to solve problems automatically. Expert systems have the ability to mimic the thinking process of experts in analyzing symptoms of damage and providing relevant solution recommendations (Al-Ayubi, 2024; Aldo et al., 2022). One method that can be implemented in the development of expert systems is Decision Tree. This method enables a systematic, structured, and easy-to-understand decision-making process through visual representations in the form of nodes and decision branches. Thus, the application of Decision Tree in expert systems not only increases the efficiency of the diagnosis process but also provides transparency of analysis results that are easier to interpret by lay users (Fadlu Rahman et al., 2024; Sulistyowati, M.Kom, Sunarto, 2024). Therefore, this study focuses on developing an expert system to diagnose EDC cash register malfunctions using the Decision Tree method, with a case study at Jinjja Chicken Center Point Restaurant in Medan, as an effort to improve the effectiveness and efficiency of handling EDC problems in the retail and food service sectors (Chogugudza, 2022; Ghiasi, 2020; Labadie, 2021; Witoelar et al., 2021).

Although EDC machines have become the backbone of cashless transactions, the reality on the ground shows that these devices are still prone to various forms of disruption, both technical and non-technical. Common problems include program errors, display errors, total machine shutdowns, idle lines, and “please try again” notifications. Each of these disruptions can cause significant obstacles in the payment process, especially in the restaurant sector, which requires speed and accuracy in transactions. Unfortunately, the process of diagnosing and handling EDC problems still relies on manual mechanisms involving technicians from the service provider. This causes delays in problem resolution, which in turn can disrupt business operations and reduce customer satisfaction. In this context, there is an urgent need for a system that can diagnose EDC machine malfunctions automatically, quickly, and accurately, while providing solution recommendations that can be implemented by non-expert users. Furthermore, the system must be able to mimic the decision-making process of an expert so that it can reduce dependence on external technicians. Therefore, this study aims to answer three main questions: (1) how to systematically identify and diagnose EDC machine malfunctions, (2) how to apply the Decision Tree method as an approach in an expert system to address these issues, and (3) to what extent the developed system can function as a substitute for experts in providing fast, accurate, and easily accessible diagnoses to users.

A number of previous studies have attempted to develop expert systems for diagnosing EDC machine malfunctions using different methodological approaches. A study conducted by Hatta, Heliza Rahmania, et al (2021), for example, designed a Forward Chaining-based expert system using 30 symptom data and 11 damage data. This study successfully demonstrated that the Forward Chaining method is effective in adopting expert knowledge to systematically detect types of EDC damage. However, this approach is still procedural and tends to require a fairly complex knowledge base when the number of symptoms increases, thereby potentially reducing the efficiency of the system. On the other hand, research conducted by Tan, Qiong, et al (2022) applied the Naïve Bayes Classifier for EDC device damage classification in gas station environments. The results of this study showed quite good performance with an accuracy of 90%, precision of 88.33%, and recall of 91.67%. These findings confirm that Naïve Bayes excels in terms of computational efficiency, but this method is highly dependent on the assumption of independence between features, which is often not fulfilled in real-world contexts.

Although both studies make significant contributions, they still leave room for development. The Forward Chaining approach is limited in terms of the interpretability of analysis results, while Naïve Bayes, although accurate, lacks transparency in the decision-making process. In this case, the Decision Tree method offers potential advantages because it is able to present knowledge representation in the form of a tree structure that is intuitive, transparent, and easy to understand by non-technical users. Thus, this study aims to fill this gap by adopting the Decision Tree method in an expert system for diagnosing EDC cash register malfunctions, thereby combining diagnostic accuracy with ease of interpretation and operational efficiency in restaurants.

Based on previous problems and research findings, this study aims to develop an expert system capable of diagnosing EDC cash register malfunctions more effectively and efficiently (Aorora, 2022). Specifically, this study is directed toward achieving three main objectives. First, to formulate a systematic approach to identifying and resolving problems arising from EDC machine malfunctions, both hardware and software. Second, to apply the Decision Tree method as the main framework in building a diagnostic model, utilizing its advantages in presenting a decision-making process that is transparent, hierarchical, and easy to understand by non-technical users. Third, to produce a computer-based system that can mimic the ability of experts to provide quick and accurate diagnoses, thereby reducing dependence on external technicians and improving restaurant operational efficiency. By achieving these objectives, this research is expected to not only contribute theoretically to the development of Decision Tree-based expert systems, but also provide practical benefits for businesses that rely on EDC machines as a vital component in supporting cashless transaction services.

Although a number of previous studies have successfully developed expert systems for diagnosing EDC machine malfunctions using various approaches, there are still several gaps that have not been optimally filled. Forward Chaining-based research tends to produce long and complex inference processes when the number of symptoms increases, thereby reducing the efficiency of the system and making it difficult for non-technical users to understand the diagnosis results (Rachman, 2019; Sapriadi et al., 2023). Meanwhile, research using the Naïve Bayes Classifier approach has proven to have high accuracy performance, but its limitation lies in the assumption of independence between features, which in the context of EDC machine malfunctions is not always realistic (Adeloju et al., 2021; Hari Agus Prastyo et al., 2024; Pokhrel, 2024). In addition, this method lacks transparency in the decision-making process, making it difficult to interpret for lay users who need a logical explanation of the diagnosis results. Thus, there is a need to develop a model that is not only capable of producing accurate diagnoses, but also presents a decision-making process that is more intuitive, transparent, and applicable in everyday operational contexts. It is in this framework that the application of the Decision Tree method becomes relevant, as it is capable of presenting knowledge representation in the form of a decision tree that is easier to understand, while providing a balance between accuracy, efficiency, and interpretability.

This study offers novelty through the application of the Decision Tree method in an expert system for diagnosing EDC cash register malfunctions, an approach that has not been widely explored in the relevant literature to date. Unlike previous studies that focused on Forward Chaining and Naïve Bayes Classifier, this study emphasizes the ability of Decision Tree to present a decision-making process that is more transparent, easy to trace, and interpretable by non-technical users. This makes the system not only function as an automatic diagnostic tool, but also as an educational medium that helps users understand the logic behind the diagnostic results. In terms of justification, this research is important because it theoretically enriches scientific knowledge in the field of expert systems by presenting an alternative approach that emphasizes interpretability and affordability. Practically, the developed system can make a real contribution to the retail and food service sectors, particularly in improving operational efficiency and reducing dependence on external technicians. The implementation of Decision Tree also enables the acceleration of the EDC machine fault diagnosis process, thereby minimizing potential losses due to delays in cashless transactions and improving service quality for customers. Thus, this research not only provides academic contributions but also has high practical relevance in supporting the digitalization of reliable and sustainable payment systems.

## Method

This research methodology was systematically designed to develop an expert system for diagnosing EDC cash register malfunctions using the Decision Tree method, starting from problem identification to final evaluation (Ghiasi, 2020; wilson, 2024; Witoelar et al., 2021). The initial stage, problem identification, was carried out by analyzing the background, objectives, and limitations of the research so that the focus remained on relevant issues, such as program errors, display errors, total machine shutdowns, line idles, and "please try again" messages. Next, the theoretical review stage was conducted to build a conceptual and methodological foundation through a review of literature related to expert systems, Decision Trees, and relevant previous research, thereby providing guidelines for designing the diagnostic model. The data collection stage includes interviews with technicians and operators, observation of EDC machine operations, and questionnaires designed to obtain accurate quantitative and qualitative data. The collected data was then analyzed systematically to identify patterns, relationships between variables, and critical symptoms, so that it could be used in compiling a knowledge base and decision tree rules. The testing and implementation stage was carried out to assess the validity of the system, including diagnostic accuracy, process efficiency, and system response to various disturbance scenarios, as well as to ensure optimal integration and user interface. Finally, an evaluation stage is conducted to assess the success of the system, draw conclusions about its strengths and limitations, and formulate suggestions for improvement and further development, so that this research not only produces a theoretical model, but also an effective and efficient practical application that can improve the operational quality of restaurants and cashless transaction services.

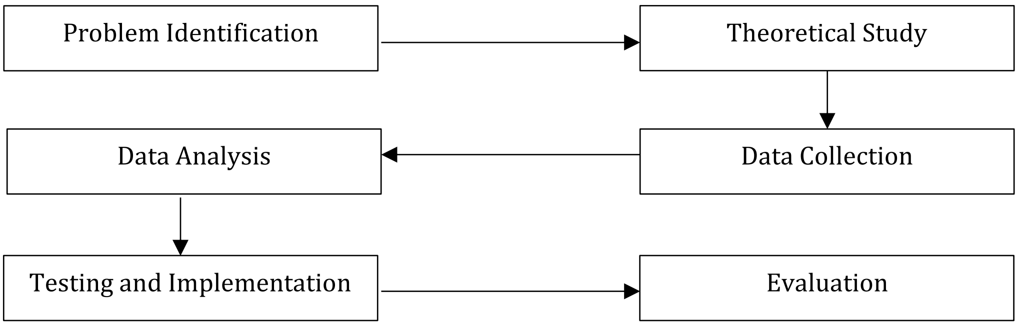


Figure 1. Research Workflow

1. Problem Identification
The problem identification stage is an important first step in researching an expert system for diagnosing EDC cash register malfunctions. At this stage, researchers map out problems in the field, including the types of damage, frequency of malfunctions, and their impact on the smooth running of transactions. The objectives and benefits of the research are formulated to ensure a relevant contribution to restaurant managers, technicians, and the development of scientific knowledge. Research limitations are determined to keep the focus controlled, distinguishing between core and additional problems. This process forms the basis for formulating research questions, data collection, analysis, and implementation of the expert system, so that the research is systematic and focused, as well as academically and practically relevant.

2. Theoretical Study
The theoretical review stage is an important foundation in researching the expert system for diagnosing EDC cash register malfunctions, providing a conceptual and methodological framework that supports system analysis and development. Researchers reviewed relevant literature from books, journals, research reports, and online sources to understand the concepts of expert systems, the Decision Tree method, and the characteristics of EDC machines. The study covers the definition of expert systems, decision tree principles, decision-making algorithms, and previous research related to EDC machine fault diagnosis. The results of the study are used to design models, define variables, compile decision tree

logic, and identify important parameters, so that the research is based on scientific evidence and has high validity.

3. Data Collection
The data collection stage is an important step in researching the EDC cash register machine malfunction diagnosis expert system, as it forms the basis for system analysis and development. Researchers used interviews, observations, and questionnaires to obtain accurate and reliable data. Interviews with technicians, operators, and restaurant owners explored the symptoms of damage, frequency of malfunctions, and handling procedures. Observations monitored the direct operation of the machines, while questionnaires collected quantitative data from respondents regarding the types of malfunctions and performance variables. The data was categorized and verified to ensure consistency, thereby supporting the creation of an accurate Decision Tree model and an applicable expert system.

4. Data Analysis
The data analysis stage is important in researching the EDC cash register machine malfunction diagnosis expert system, because it processes information for system development. Data from interviews, observations, and questionnaires are categorized according to variables such as the type of malfunction, frequency, and contributing factors. Systematic analysis is carried out to identify patterns of relationships between variables, dominant symptoms, and the consistency of information from various sources. The results are used to build a knowledge base and decision rules in a Decision Tree model, covering both quantitative and qualitative data. This stage ensures that the expert system is relevant, applicable, accurate, fast, and reliable, while also providing a basis for validating implementation in the field.

5. Testing and Implementation
The testing and implementation stages are important to ensure that the EDC cash register malfunction diagnosis expert system functions according to the research objectives. The Decision Tree model was tested using independent data to assess the accuracy and reliability of the diagnosis. Implementation was carried out at the Jinjja Chicken Center Point restaurant in Medan, covering functionality testing, database integration, and user interface. The test results evaluated response time efficiency, accuracy compared to manual methods, and identified weaknesses or bugs. This process provided practical insights for system refinement, confirmed scientific validity, and ensured practical relevance, so that the system could be relied upon to improve operational efficiency and speed up diagnosis.

6. Evaluation
The evaluation stage plays an important role in assessing the effectiveness of the EDC cash register malfunction diagnosis expert system. Researchers analyzed the results of testing and implementation, including diagnostic accuracy, process speed, and ease of use. The system's performance was compared with manual methods or conventional expert practices to assess its ability to replace the role of experts. The evaluation also highlights aspects of practicality, interface, database integration, and system response to various disturbances. Based on the findings, researchers draw conclusions about the strengths, limitations, and suggestions for system development. This stage ensures that the research produces practical applications that improve operational efficiency, reduce technician dependence, and enhance service quality.

## Results and Discussions

The damage table will be used as a question that users can choose from. The damage table contains the names of damages found in the system. The table structure can be seen as follows :

Table 1. Damage

| Code | Damage Name |
|---|---|
| K01 | Program Error |

| | |
|---|---|
| K02 | Display Error |
| K03 | EDC Completely Dead |
| K04 | Button Damage |
| K05 | Printer Error |
| K06 | Encryption Error |
| K07 | Card Fail/Error |
| K08 | Waiting For Line |

The damage symptom table is a table used to receive input from users before performing the damage detection process. The damage symptom selection process will determine the type of damage to be used. The table structure can be seen as follows:

Table 2. Symptoms of damage to the EDC Cashier machine

| Symptom Code | Symptom |
|---|---|
| G01 | EDC Error Display Description: Invalid Terminal Key |
| G02 | EDC Error Display Description: Security Error Code: 1 |
| G03 | EDC Error Display Description: Alert Interruption |
| G04 | EDC Software Corrupted |
| G05 | EDC Menu Display Abnormal |
| G06 | EDC Display Turns On and Off Continuously |
| G07 | EDC Not Receiving Power |
| G08 | EDC Adapter Damaged |
| G09 | EDC adapter is incompatible |
| G10 | EDC is completely damaged due to water submersion/fall |
| G11 | Button connector rubber is not connected to the PCB |
| G12 | EDC button connector rubber is damaged |
| G13 | EDC invoice is out of stock/invoice is not installed |
| G14 | EDC Menu Display is Abnormal |
| G15 | EDC Printer Hardware is Damaged |
| G16 | Incorrectly inserted debit/credit card pin |
| G17 | Incorrectly pressed function button on EDC printer |
| G18 | EDC magnetic swipe error |
| G19 | EDC stripe insertion error |
| G20 | Telephone line not connected/incorrect port placement |
| G21 | Telephone line disconnected/disconnected from other parallel sockets |
| G22 | Paralleled telephone line is in use |
| G23 | Telkom fees have not been paid |
| G24 | Perform EDC PABX settings |
| G25 | EDC provider blocked / telephone fees have not been paid |
| G26 | Problem is more likely caused by telephone communication and provider |
| G27 | Problem occurs on the line side before processing |
| G28 | Different telephone line type settings |
| G29 | EDC blocked inactive |
| G30 | Provider settings are not correct |

All data on damage and symptoms of damage to EDC cash registers will be linked to form an expert rule. Based on the damage relationships in Table 3, there is an expert rule whose results are then loaded to be encoded into programming language. Below is a table of the knowledge base (Rule Base) for diagnosing damage to EDC cash registers.

Table 3. Rule Based

| Code | EDC Machine Malfunction Name | Gejala |
|---|---|---|
| K01 | Program Error | G01, G02, G03, G04 |
| K02 | Display Error | G03, G05, G06 |
| K03 | EDC Completely Dead | G07, G08, G09, G10, |
| K04 | Button Malfunction | G11, G12, G14 |
| K05 | Printer Error | G08, G13, G15, |
| K06 | Encryption Error | G16, G17, G18 |
| K07 | Card Failure/Error | G19, G18 |
| K08 | Waiting for Line | G21, G22, G20, G23 |
| K09 | Idle Line | G24, G25, G26 |
| K10 | Please try again-TO | G27, G28, G29, |
| K11 | Please try again-CE | G28, G30 |

A knowledge base table is a table used to perform calculations and also serves as a basis for decision making. The knowledge base table contains information about the relationship between damage and symptoms found in the system. The structure of the knowledge base table can be seen in Table 4.

Table 4. The structure of the knowledge base

| No | | G 01 | G 02 | G 03 | G 04 | G 05 | G 06 | G 07 | G 08 | G 09 | G 10 | G 29 | … | G 30 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | K1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … | 0 |
| 2 | K1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | … | 0 |
| 3 | K2 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | … | 0 |
| 4 | K2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … | 0 |
| 5 | K3 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | … | 0 |
| 6 | K4 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | … | 0 |
| 7 | K4 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … | 0 |
| 8 | K5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | … | 0 |
| 9 | K6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … | 0 |
| 10 | K7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … | 1 |
| 11 | K8 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … | 0 |
| 12 | K09 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | … | 0 |
| 13 | K10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … | 0 |
| 14 | K11 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | … | 0 |
| 15 | K11 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … | 0 |

The calculation process uses the concepts of entropy and information gain. The first process begins by calculating the entropy of the damage, referred to as H(Y). Next, the entropy of each value in each symptom is calculated, referred to as H(Y|X=value). After that, the entropy of each EDC cash register machine damage symptom is sought, referred to as H(Y|X). Based on the values of H(Y) and H(Y|X), the information gain value of each symptom is found, referred to as IG(Y|X).

Table 5. Amount of Damage Data

| No | Name of Damage | Quantity |
|---|---|---|
| 1 | K01 | 2 |
| 2 | K02 | 2 |
| 3 | K03 | 1 |
| 4 | K04 | 2 |
| 5 | K05 | 1 |
| 6 | K06 | 1 |
| 7 | K07 | 1 |
| 8 | K08 | 1 |

| | | |
|---|---|---|
| 9 | K09 | 1 |
| 10 | K10 | 1 |
| 11 | K11 | 2 |
| | Quantity | 15 |

H(Y) = - 2/15 $\log_2$ (2/15) - 2/15 $\log_2$ (2/15) - 1/15 $\log_2$ (1/15) - 2/15 $\log_2$ (2/15) - 1/15 $\log_2$ (1/15) - 1/15 $\log_2$ (1/15) - 1/15 $\log_2$ (1/15) - 1/15 $\log_2$ (1/15) - 1/15 $\log_2$ (1/15) - 1/15 $\log_2$ (1/15) 2/15 $\log_2$ (2/15)
= 2,33

Information gain for X1 = Program Error with Yes = 4 and No = 11 can be calculated as follows;
H(Y|$X_1$ = Ya) = - 1/4 $\log_2$ 1/4 - 1/4 $\log_2$ 1/4 - 1/4 $\log_2$ 1/4- 1/4 $\log_2$ 1/4 = 2

H(Y|$X_1$ = No) = - 2/11 $\log_2$ (2/11) - 2/11 $\log_2$ (2/11) - 1/11 $\log_2$ (1/11) - 2/11 $\log_2$ (2/11) - 1/15 $\log_2$ (1/11) - 1/11 $\log_2$ (1/11) - 1/11 $\log_2$ (1/11) - 1/11 $\log_2$ (1/11) - 1/11 $\log_2$ (1/11) - 1/11 $\log_2$ (1/11) 2/15 $\log_2$ (2/11)
= 2,78

H(Y|$X_1$) = 4/15 (2) + (11/15) (2,78) = 2,57
IG(Y|$X_1$) = 2,78 – 2,57 = 0,21

The information gain for X2 = Display Error with Yes = 3 and No = 12 can be calculated as follows:
H(Y|$X_1$ = Yes) = - 1/3 $\log_2$ 1/3 - 1/3 $\log_2$ 1/3 - 1/3 $\log_2$ 1/3- 1/3 $\log_2$ 1/3 = 2

H(Y|$X_1$ = No) = - 2/13 $\log_2$ (2/13) - 2/13 $\log_2$ (2/13) - 1/13 $\log_2$ (1/13) - 2/13 $\log_2$ (2/13) - 1/13 $\log_2$ (1/13) - 1/13 $\log_2$ (1/13) - 1/13 $\log_2$ (1/13) - 1/13 $\log_2$ (1/13) - 1/13 $\log_2$ (1/13) - 1/13 $\log_2$ (1/13) 2/15 $\log_2$ (2/13)
= 2,54

H(Y|$X_1$) = 3/15 (2) + (12/15) (2,54) = 2,43
IG(Y|$X_1$) = 2,54 – 2,43 = 0,11

Information gain for X3 = EDC Total Death with Yes = 3 and No = 12 can be calculated as follows:
H(Y|$X_1$ = Yes) = - 1/3 $\log_2$ 1/3 - 1/3 $\log_2$ 1/3 - 1/3 $\log_2$ 1/3- 1/3 $\log_2$ 1/3 = 2

H(Y|$X_1$ = No) = - 2/13 $\log_2$ (2/13) - 2/13 $\log_2$ (2/13) - 1/13 $\log_2$ (1/13) - 2/13 $\log_2$ (2/13) - 1/13 $\log_2$ (1/13) - 1/13 $\log_2$ (1/13) - 1/13 $\log_2$ (1/13) - 1/13 $\log_2$ (1/13) - 1/13 $\log_2$ (1/13) - 1/13 $\log_2$ (1/13) 2/15 $\log_2$ (2/13)
= 2,54

H(Y|$X_1$) = 3/15 (2) + (12/15) (2,54) = 2,43
IG(Y|$X_1$) = 2,54 – 2,43 = 0,11

Information gain for X4 = Button Damage with Yes = 4 and No = 11 can be calculated as follows :
H(Y|$X_1$ = Yes) = - 1/4 $\log_2$ 1/4 - 1/4 $\log_2$ 1/4 - 1/4 $\log_2$ 1/4- 1/4 $\log_2$ 1/4 = 2

H(Y|$X_1$ = No) = - 2/11 $\log_2$ (2/11) - 2/11 $\log_2$ (2/11) - 1/11 $\log_2$ (1/11) - 2/11 $\log_2$ (2/11) - 1/15 $\log_2$ (1/11) - 1/11 $\log_2$ (1/11) - 1/11 $\log_2$ (1/11) - 1/11 $\log_2$ (1/11) - 1/11 $\log_2$ (1/11) - 1/11 $\log_2$ (1/11) 2/15 $\log_2$ (2/11)
= 2,78

$H(Y|X_1) = 4/15\ (2) + (11/15)\ (2{,}78) = 2{,}57$
$IG(Y|X_1) = 2{,}78 - 2{,}57 = 0{,}21$

The information gain for X5 = Printer Error with Yes = 3 and No = 12 can be calculated as follows:
$H(Y|X_1 = Yes) = -\ 1/3 \log_2 1/3 - 1/3 \log_2 1/3 - 1/3 \log_2 1/3 - 1/3 \log_2 1/3 = 2$

$H(Y|X_1 = No) = -\ 2/13 \log_2 (2/13) - 2/13 \log_2 (2/13) - 1/13 \log_2 (1/13) - 2/13 \log_2 (2/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13)\ 2/15 \log_2 (2/13)$
$= 2{,}54$

$H(Y|X_1) = 3/15\ (2) + (12/15)\ (2{,}54) = 2{,}43$
$IG(Y|X_1) = 2{,}54 - 2{,}43 = 0{,}11$

Information gain for X6 = Encryption Error with Yes = 2 and No = 13 can be calculated as follows :
$H(Y|X_1 = Yes) = -\ 1/2 \log_2 1/2 - 1/2 \log_2 1/2 - 1/2 \log_2 1/24 - 1/2 \log_2 1/2 = 4$

$H(Y|X_1 = No) = -\ 2/13 \log_2 (2/13) - 2/13 \log_2 (2/13) - 1/13 \log_2 (1/13) - 2/13 \log_2 (2/13) - 1/13 \log_2 (1/13) - 1/11 \log_2 (1/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13)\ 2/13 \log_2 (2/13)$
$= 2{,}53$

$H(Y|X_1) = 4/15\ (4) + (13/15)\ (2{,}53) = 3{,}25$
$IG(Y|X_1) = 3{,}25 - 2{,}53 = 0{,}72$

Information gain for X7 = Card Fail/Error with Yes = 3 and No = 12 can be calculated as follows:
$H(Y|X_1 = Yes) = -\ 1/3 \log_2 1/3 - 1/3 \log_2 1/3 - 1/3 \log_2 1/3 - 1/3 \log_2 1/3 = 2$

$H(Y|X_1 = No) = -\ 2/13 \log_2 (2/13) - 2/13 \log_2 (2/13) - 1/13 \log_2 (1/13) - 2/13 \log_2 (2/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13) - 1/13 \log_2 (1/13)\ 2/15 \log_2 (2/13)$
$= 2{,}54$

$H(Y|X_1) = 3/15\ (2) + (12/15)\ (2{,}54) = 2{,}43$
$IG(Y|X_1) = 2{,}54 - 2{,}43 = 0{,}11$

The information gain for X8 = Waiting For Line with Yes = 4 and No = 11 can be calculated as follows :
$H(Y|X_1 = Yes) = -\ 1/4 \log_2 1/4 - 1/4 \log_2 1/4 - 1/4 \log_2 1/4 - 1/4 \log_2 1/4 = 2$

$H(Y|X_1 = No) = -\ 2/11 \log_2 (2/11) - 2/11 \log_2 (2/11) - 1/11 \log_2 (1/11) - 2/11 \log_2 (2/11) - 1/15 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11)\ 2/15 \log_2 (2/11)$
$= 2{,}78$

$H(Y|X_1) = 4/15\ (2) + (11/15)\ (2{,}78) = 2{,}57$
$IG(Y|X_1) = 2{,}78 - 2{,}57 = 0{,}21$

The information gain for X9 = Line Idle with Yes = 7 and No = 8 can be calculated as follows:
$H(Y|X_1 = Yes) = -\ 1/7 \log_2 1/7 - 1/7 \log_2 1/7 - 1/7 \log_2 1/7 - 1/7 \log_2 1/7 = 2$

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H(Y|X1 = No) = - 2/8 log2 (2/8) - 2/8 log2 (2/8) - 1/8 log2 (1/8) - 2/8 log2 (2/8) - 1/8 log2 (1/8) - 1/8 log2 (1/8) - 1/8 log2 (1/8) - 1/8 log2 (1/8) - 1/8 log2 (1/8) - 1/8 log2 (1/8) 2/8 log2 (2/8)
= 3,25

H(Y|X1) = 7/15 (2) + (8/15) (3,25) = 2,66
IG(Y|X1) = 3,25– 2,66 = 0,59

Information gain for X10 = Please try again-TO with Yes = 4 and No = 11 can be calculated as follows
H(Y|X1 = Yes) = - 1/4 log2 1/4 - 1/4 log2 1/4 - 1/4 log2 1/4- 1/4 log2 1/4 = 2

H(Y|X1 = No) = - 2/11 log2 (2/11) - 2/11 log2 (2/11) - 1/11 log2 (1/11) - 2/11 log2 (2/11) - 1/15 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) 2/15 log2 (2/11)
= 2,78

H(Y|X1) = 4/15 (2) + (11/15) (2,78) = 2,57
IG(Y|X1) = 2,78 – 2,57 = 0,21

The information gain for X11 = Please Try Again-CE with Yes = 5 and No = 10 can be calculated as follows:
H(Y|X1 =Yes) = - 1/5 log2 1/5 - 1/5 log2 1/5 - 1/5 log2 1/5- 1/5 log2 1/5 = 2

H(Y|X1 = No) = - 2/10 log2 (2/10) - 2/10 log2 (2/10) - 1/10 log2 (1/10) - 2/10 log2 (2/10) - 1/10 log2 (1/10) - 1/10 log2 (1/10) - 1/10 log2 (1/10) - 1/10 log2 (1/10) - 1/10 log2 (1/10) - 1/10 log2 (1/10) 2/10 log2 (2/10)
= 3,25

H(Y|X1) = 5/15 (2) + (10/15) (3,25) = 2,83
IG(Y|X1) = 3,25 – 2,83 = 0,42

Information gain for X12 = Line Idle Yes = 4 and No = 11 can be calculated as follows:
H(Y|X1 = Yes) = - 1/4 log2 1/4 - 1/4 log2 1/4 - 1/4 log2 1/4- 1/4 log2 1/4 = 2

H(Y|X1 = No) = - 2/11 log2 (2/11) - 2/11 log2 (2/11) - 1/11 log2 (1/11) - 2/11 log2 (2/11) - 1/15 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) 2/15 log2 (2/11)
= 2,78

H(Y|X1) = 4/15 (2) + (11/15) (2,78) = 2,57
IG(Y|X1) = 2,78 – 2,57 = 0,21

The information gain for X13 = Please Try Again-To Ya = 4 and No = 11 can be calculated as follows:
H(Y|X1 = Yes) = - 1/4 log2 1/4 - 1/4 log2 1/4 - 1/4 log2 1/4- 1/4 log2 1/4 = 2

H(Y|X1 = No) = - 2/11 log2 (2/11) - 2/11 log2 (2/11) - 1/11 log2 (1/11) - 2/11 log2 (2/11) - 1/15 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) - 1/11 log2 (1/11) 2/15 log2 (2/11)
= 2,78

H(Y|X1) = 4/15 (2) + (11/15) (2,78) = 2,57

$IG(Y|X_1) = 2{,}78 – 2{,}57 = 0{,}21$

The information gain for X14 = Please Try Again-CE Yes = 4 and No = 11 can be calculated as follows:

$H(Y|X_1 = Yes) = - 1/4 \log_2 1/4 - 1/4 \log_2 1/4 - 1/4 \log_2 1/4 - 1/4 \log_2 1/4 = 2$

$H(Y|X_1 = No) = - 2/11 \log_2 (2/11) - 2/11 \log_2 (2/11) - 1/11 \log_2 (1/11) - 2/11 \log_2 (2/11) - 1/15 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11)\ 2/15 \log_2 (2/11)$
$= 2{,}78$

$H(Y|X_1) = 4/15\ (2) + (11/15)\ (2{,}78) = 2{,}57$
$IG(Y|X_1) = 2{,}78 – 2{,}57 = 0{,}21$

Information gain for X15 = Please Try Again-CE Yes = 4 and No = 11 can be calculated as follows:

$H(Y|X_1 = Yes) = - 1/4 \log_2 1/4 - 1/4 \log_2 1/4 - 1/4 \log_2 1/4 - 1/4 \log_2 1/4 = 2$

$H(Y|X_1 = No) = - 2/11 \log_2 (2/11) - 2/11 \log_2 (2/11) - 1/11 \log_2 (1/11) - 2/11 \log_2 (2/11) - 1/15 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11) - 1/11 \log_2 (1/11)\ 2/15 \log_2 (2/11)$
$= 2{,}78$

$H(Y|X_1) = 4/15\ (2) + (11/15)\ (2{,}78) = 2{,}57$
$IG(Y|X_1) = 2{,}78 – 2{,}57 = 0{,}21$

Table 6. Information Gain

| No | Name of Damage | Information Gain |
|---|---|---|
| 1 | $X_1$ = Program Error | 0,21 |
| 2 | $X_2$ = Display Error | 0,11 |
| 3 | $X_3$ = EDC Mati Total | 0,11 |
| 4 | $X_4$ Button Malfunction | 0,21 |
| 5 | $X_5$ = Printer Error | 0,11 |
| 6 | $X_6$ = Ecyription Error | 0,72 |
| 7 | $X_7$ = Card Fail/Error | 0,11 |
| 8 | $X_8$ = Waiting For Line | 0,21 |
| 9 | $X_9$ = Line Iddle | 0,59 |
| 10 | $X_{10}$ = Please try again-TO | 0,21 |
| 11 | $X_{11}$ = Please Try Again-CE | 0,42 |
| 12 | Line Iddle | 0,21 |
| 13 | Please Try Again-TO | 0,21 |
| 14 | Please Try Again-CE | 0,21 |
| 15 | Please Try Again-CE | 0,21 |

The highest information gain is Ecyription Error, therefore Ecyription Error is used as the root. Since Ecyription Error still has two values, yes and no, the process is repeated for Ecyription Error yes and Ecyription Error no.

To diagnose EDC machine malfunctions, it is necessary to first identify the most common malfunctions. Although there are only five types of malfunctions, namely Program Error, Display Error, Total EDC Failure, Line Idle, and Please Try Again, they are very helpful for calculations in the Decision Tree method applied in this system. Implementation is a continuation of the system design activities. This stage involves setting up the system so that it is ready for operation and can be seen as an effort to realize the designed system. The steps in this stage are a sequence of activities from start to finish that must be carried out in order to realize the designed system. The result of the implementation of the system developed from this thesis is an expert system for diagnosing EDC machine malfunctions. The expert system for diagnosing EDC machine malfunctions has several forms, namely the Login form, the Analysis form, and the About form for managing data. After the system design was completed, the author presented the results of the designed system in the form of a display. The following is the interface design and explanation that the author designed

This main page is the initial page when accessing the expert system for diagnosing EDC machine malfunctions. On the initial page, there is also a user menu, namely Start Analysis, About, Exit/Login.

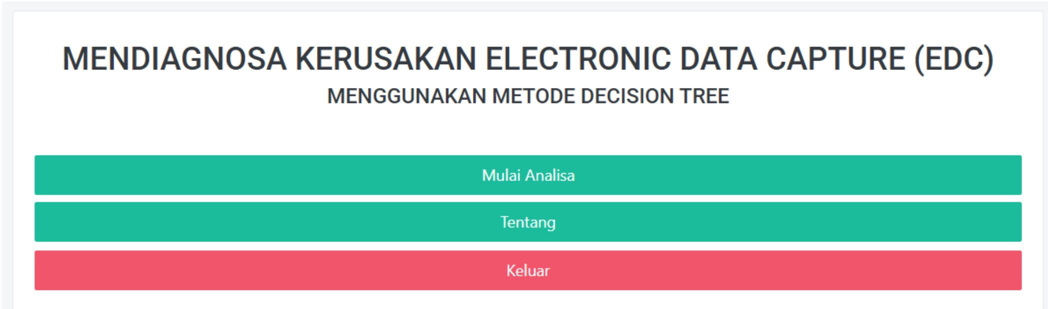


Figure 2. Main Page

In the symptom menu, users or system users can select the symptoms that occur and, from the test results, select the symptoms that cause EDC machine malfunctions so that they can diagnose the EDC machine malfunction.

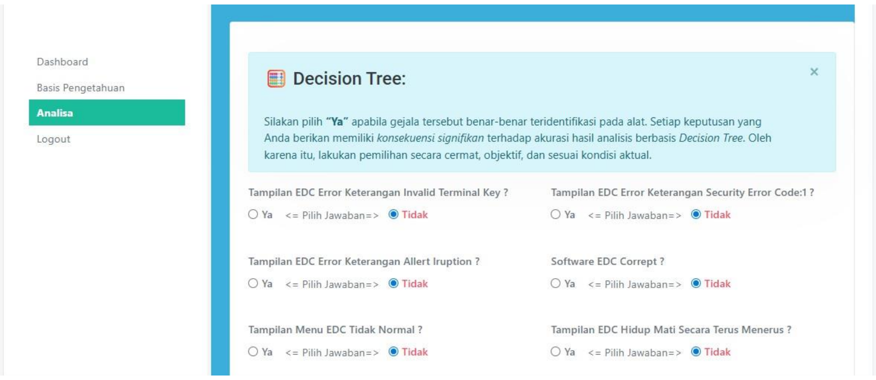


Figure 3. Select Symptoms Menu

The dataset in the expert system for diagnosing EDC machine malfunctions contains a collection of data that includes symptoms of malfunctions, possible causes (malfunctions/damage), and the relationship between the two, which will later be used by the inference engine to generate a diagnosis.

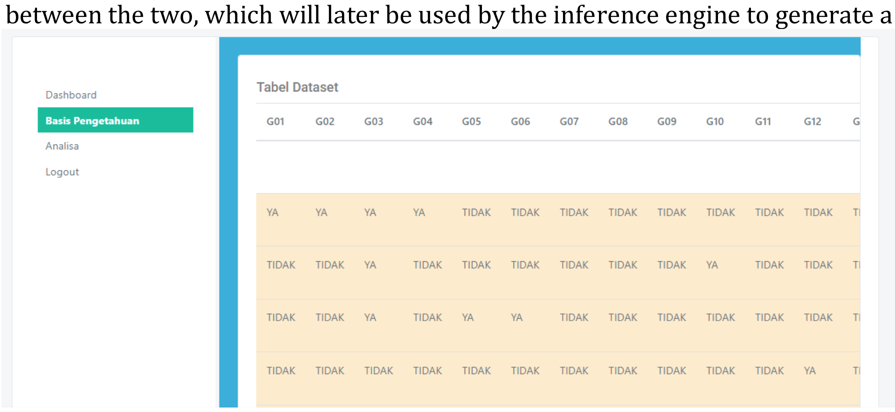


Figure 4. EDC Machine Malfunction Dataset

This form is the result of calculations of EDC machine malfunctions that have been entered by the user. It contains the results from the expert system using the Decision Tree method entered by the user.

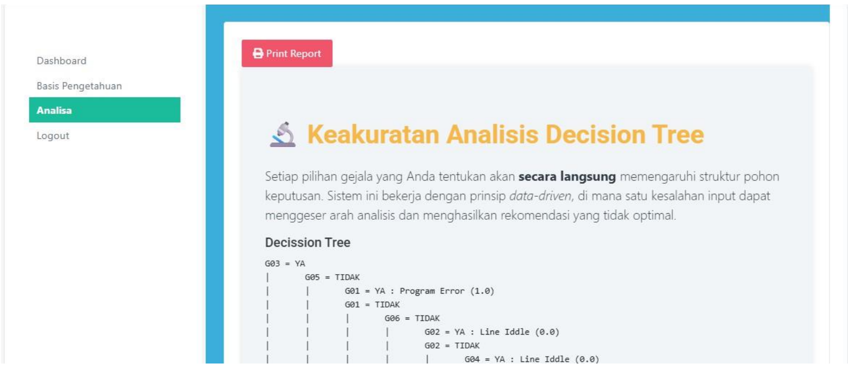


Figure 5. Diagnosis Results Menu

Discussion

The results show that the developed expert system is capable of diagnosing EDC cash register malfunctions based on symptoms selected by users. The compilation of a knowledge base through malfunction tables and symptom tables (Table 1 and Table 2) provides a clear foundation for linking each symptom with a type of malfunction (Table 3). This process is then represented in the form of a knowledge base structure (Table 4) which is used as the main reference in the inference process. Entropy and information gain calculations were performed to determine the most influential attributes in the classification process using the Decision Tree method. From the calculation results, the initial entropy value of the system was 2.33, which indicates the initial level of uncertainty in the diagnosis. Furthermore, the information gain calculation showed that Encryption Error had the highest information gain value, namely 0.72, so this attribute was selected as the root in the formation of the decision tree. This is in line with the basic principles of the C4.5 algorithm, which emphasizes the selection of attributes with the highest information gain as the main node to minimize diagnosis uncertainty.

In addition, the calculation results also show that Line Idle (IG = 0.59) and Please Try Again-CE (IG = 0.42) errors are attributes with high contributions in classification, thus playing an important role in decision tree branching. Meanwhile, faults such as Display Error, Printer Error, and Card Fail/Error have relatively low information gain values (0.11), indicating that the related symptoms do not contribute significantly to distinguishing the type of fault. The implementation of this expert system produces three main components: a login form, a symptom analysis form, and a diagnosis result form. Through this interface, users can easily select symptoms that correspond to the EDC malfunction they are experiencing. The diagnosis results are displayed in the form of an output containing the type of malfunction and its causative symptoms. Thus, this system not only helps technicians speed up the malfunction identification process, but also reduces the risk of misdiagnosis that often occurs when done manually. Compared to conventional diagnosis methods, the use of Decision Trees in this expert system provides the main advantages of speed, accuracy, and transparency in decision making. The decision tree structure that is formed can be traced back so that the reasons for selecting the type of damage can be explained logically. This is an added value in the application of expert systems in restaurant operations, especially to support the smooth running of cashless transactions that are highly dependent on the performance of EDC cash registers.

Overall, this study confirms that the combination of rule-based knowledge with the Decision Tree algorithm is effective in developing an expert system for diagnosing EDC cash register damage. However, this research is still limited to a dataset of symptoms and malfunctions that have been defined beforehand. In the next stage, the system can be developed by adding more real-world data and applying other optimization methods such as Random Forest or Support Vector Machine (SVM) to improve classification accuracy.

## Conclusions

This study successfully developed and applied the Decision Tree method in an expert system to diagnose malfunctions in Electronic Data Capture (EDC) cash registers at Jinjja Chicken Center Point restaurants. The results of analysis and testing show that this expert system is capable of diagnosing EDC malfunctions with a high degree of accuracy, thereby supporting the technical team in identifying problems more quickly and accurately. The application of this system has been proven to improve operational efficiency by reducing the time needed to detect and handle cash register malfunctions, which has a positive impact on restaurant operations and customer satisfaction. The Decision Tree algorithm has been proven effective as an inference method in expert systems for EDC malfunction cases, as it is capable of managing various complex symptoms and conditions and producing decision rules that are easy for users to understand. This research also opens up opportunities for further development, including integration with other optimization methods or application to more diverse EDC devices, thereby increasing the predictive capabilities and flexibility of expert systems. Overall, this research makes a significant contribution both theoretically, through the application of the Decision Tree algorithm to expert systems, and practically, in improving the reliability and operational efficiency of EDC cash registers in restaurant environments.

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