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# Decision Tree-Based Web Expert System for Preliminary Screening of Refractive Eye Disorders

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**ABSTRACT**

Refractive eye disorders remain one of the leading causes of visual impairment worldwide, while limited access to ophthalmology services often delays early diagnosis. This study investigates the effectiveness of the Decision Tree algorithm for symptom-based classification of refractive eye disorders and its implementation within a web-based expert system for preliminary eye health screening. Data were collected from 505 respondents using a structured Google Forms questionnaire. After preprocessing and labeling, the dataset was divided into 80% training data and 20% testing data. Model performance was evaluated using a confusion matrix together with accuracy, precision, recall, and F1-score metrics to provide a comprehensive assessment under an imbalanced class distribution. Experimental results showed that the proposed Decision Tree model achieved an overall accuracy of 89.11% and demonstrated satisfactory performance in identifying dominant diagnostic classes while maintaining transparent and interpretable decision rules. The developed web-based system provides symptom-based diagnosis, examination history management, and PDF report generation to support preliminary eye health assessment. These findings indicate that the proposed approach is suitable as an accessible decision-support tool for preliminary refractive eye disorder screening, particularly in areas with limited access to ophthalmology services.

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## I. Introduction

The eye is one of the most important sensory organs in human life because it enables individuals to obtain visual information from their surroundings. Visual impairment can negatively affect educational activities, work productivity, social interaction, and overall quality of life. One of the most common causes of visual impairment is refractive error, which includes myopia, hyperopia, astigmatism, and presbyopia [1], [2].

According to the World Health Organization (WHO), uncorrected refractive errors remain one of the leading causes of visual impairment worldwide. Millions of people suffer from vision disorders due to delayed diagnosis and inadequate corrective treatment. In many developing countries, including Indonesia, access to eye healthcare services remains limited, particularly in rural and remote areas. Consequently, many individuals do not receive timely eye examinations, leading to reduced visual function and decreased quality of life [1], [2], [3].

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have created significant opportunities in the healthcare sector. Machine learning algorithms have been widely applied in disease prediction, medical diagnosis, image classification, and clinical decision support systems. Among various machine learning methods, the Decision Tree algorithm has become one of the most widely used classification techniques because of its simple structure, interpretability, and ability to generate understandable decision rules [4], [5], [7].

Several studies have demonstrated that artificial intelligence can assist healthcare professionals in improving diagnostic performance. In ophthalmology, machine learning techniques have been successfully applied for refractive error prediction and eye disease detection. Previous studies reported that AI-based systems can improve screening efficiency and support early diagnosis processes, thereby helping reduce the burden of visual impairment in the community [4], [5], [6].

In Indonesia, Decision Tree and C4.5 algorithms have been successfully implemented in various healthcare-related classification problems. Previous studies have utilized these algorithms for diagnosing liver disease, COVID-19 surveillance classification, hepatitis prediction, diabetes prediction, and other health-related decision support systems [11], [16]. The results indicate that Decision Tree-based approaches are capable of producing reliable classification performance and can be effectively applied in healthcare applications.

Although refractive errors can generally be corrected through eyeglasses, contact lenses, or refractive surgery, many cases remain undetected because patients often underestimate early symptoms and delay seeking professional medical examinations. This condition is particularly common in areas where ophthalmology services are limited. Therefore, the development of an accessible preliminary diagnostic system is important to support early detection and increase public awareness regarding eye health [2], [3].

The primary objective of this study is to investigate the effectiveness of the Decision Tree algorithm in classifying refractive eye disorders based on symptom data and to evaluate its applicability within a web-based expert system for preliminary eye health screening. In addition to developing the application, this study focuses on analyzing the classification performance, interpretability, and practical feasibility of integrating machine learning into an accessible diagnostic support system.

Based on the identified research problem, this study hypothesizes that the Decision Tree algorithm can effectively classify refractive eye disorders using symptom-based data while maintaining transparent decision rules and satisfactory predictive performance. Furthermore, integrating the trained model into a web-based expert system is expected to provide an accessible and practical tool for preliminary eye health screening.

Web-based diagnostic systems offer several advantages, including ease of access, platform independence, and the ability to provide preliminary diagnostic information without requiring users to install additional software. Such systems can serve as supporting tools for early detection and increase public awareness regarding eye health, especially among individuals who have limited access to ophthalmology services [4], [6].

However, despite the growing adoption of machine learning techniques in healthcare applications, studies specifically focusing on web-based expert systems for diagnosing refractive eye disorders using the Decision Tree algorithm remain relatively limited, particularly within the Indonesian context. Most existing studies have concentrated on image-based eye disease detection, general medical diagnosis, or the application of machine learning algorithms to other healthcare classification problems. Consequently, limited attention has been given to the development of symptom-based diagnostic systems that can be easily accessed by the public through web platforms while maintaining model interpretability and computational efficiency.

Furthermore, many previous studies primarily emphasize classification performance without integrating machine learning models into practical web-based diagnostic environments that support user interaction, examination history management, and diagnostic report generation. As a result, there remains a gap between algorithmic development and its practical implementation in accessible healthcare-support applications. Addressing this gap is important because early identification of refractive disorders can contribute to improved awareness, timely intervention, and better visual health outcomes, particularly in regions with limited access to ophthalmology services.

Therefore, this study proposes a web-based expert system for the early diagnosis of refractive eye disorders using the Decision Tree algorithm. The proposed system utilizes symptom-based classification to identify four common refractive disorders, namely myopia, hypermetropia, astigmatism, and presbyopia. The system is implemented using the Flask framework and integrated with a MySQL database to facilitate diagnostic processing, examination history storage, and report generation.

The contribution of this study is threefold. First, it provides an interpretable machine learning approach for diagnosing refractive eye disorders based on symptom data collected from respondents. Second, it demonstrates the implementation of a Decision Tree model within a practical web-based healthcare support system that can be accessed without requiring specialized software installation. Third, it evaluates the effectiveness of the proposed approach using standard classification metrics, thereby providing empirical evidence regarding the applicability of Decision Tree algorithms in supporting preliminary eye health diagnosis. The findings of this study are expected to contribute to the development of intelligent healthcare applications and support the broader adoption of machine learning technologies in preventive eye healthcare services.

## II. METHODOLOGY

This study employs a machine learning approach using the Decision Tree algorithm to classify refractive eye disorders. The research framework consists of six main stages, namely literature review, dataset collection, data preprocessing, model development, web-based system implementation, and performance evaluation. The overall research workflow is illustrated in Figure 1.

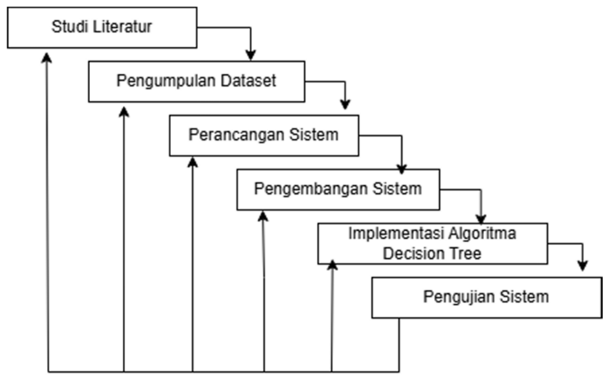


Figure 1. Research Scheme

*A. Dataset Collection*

The dataset used in this study was collected through an online questionnaire distributed using Google Forms. The questionnaire was designed to gather information regarding symptoms commonly associated with refractive eye disorders. Data collection was conducted voluntarily, and respondents were allowed to complete the questionnaire independently through an internet-connected device.

A total of 505 respondents participated in the survey. The questionnaire consisted of a series of symptom-related questions developed based on common clinical characteristics of refractive eye disorders. The collected responses included information describing visual difficulties experienced by respondents, such as blurred vision, difficulty seeing distant objects, difficulty seeing nearby objects, eye strain, headaches, and other symptoms relevant to refractive abnormalities.

The collected dataset was designed to support the classification of four categories of refractive eye disorders, namely myopia, hypermetropia, astigmatism, and presbyopia. Prior to model development, the collected responses were examined to ensure data completeness and consistency. Records containing incomplete information or invalid responses were identified and processed during the preprocessing stage to improve overall data quality.

The use of questionnaire-based data collection offers several advantages for developing a symptom-based diagnostic system. First, it enables efficient acquisition of respondent information from a relatively large population. Second, the collected symptom data can be directly utilized as input features for machine learning classification. Third, the approach reflects the practical scenario in which users perform self-assessment based on symptoms experienced before seeking professional medical consultation.

After the data collection process was completed, the dataset was prepared for further preprocessing procedures, including symptom mapping, data transformation, automatic labeling, and dataset validation. The resulting dataset served as the primary source for training and evaluating the Decision Tree classification model developed in this study.

*B. Preprocessing Data*

Data preprocessing was performed to transform the raw questionnaire responses into a structured dataset suitable for machine learning analysis. This stage plays an important role in improving data quality and ensuring that the collected information can be effectively processed by the Decision Tree algorithm. The preprocessing procedure consisted of data cleaning, symptom mapping, data transformation, automatic labeling, dataset splitting, and validation.

The first step involved data cleaning to identify incomplete responses, duplicate entries, and inconsistencies within the collected dataset. Responses containing incomplete or invalid information were identified and removed from further analysis to ensure data consistency and reliability. This procedure ensured that the dataset used for model development contained accurate and representative information.

Following the cleaning process, symptom mapping was conducted. Each questionnaire item was associated with specific refractive eye disorder characteristics based on commonly recognized symptoms. The symptoms were categorized into four diagnostic groups: myopia, hypermetropia, astigmatism, and presbyopia. This mapping process provided a structured representation of symptom patterns that could later be utilized for classification.

Because machine learning algorithms require numerical input, all categorical responses were transformed into binary numerical values. Responses indicating the presence of a symptom were assigned a value of 1, while responses indicating the absence of a symptom were assigned a value of 0. This binary representation simplifies data processing and enables efficient classification by the Decision Tree model.

After transformation, an automatic labeling process was performed to assign a diagnostic category to each respondent. The labeling procedure was conducted using a rule-based scoring mechanism. Each symptom was associated with one or more refractive eye disorder categories according to predefined diagnostic criteria. The cumulative score for each category was calculated, and the category with the highest score was assigned as the final diagnostic label. Through this procedure, each record was categorized into one of four classes: myopia, hypermetropia, astigmatism, or presbyopia.

To evaluate model performance objectively, the dataset was divided into training and testing subsets using an 80:20 hold-out strategy. Approximately 80% of the observations were utilized for model training, while the remaining 20% were reserved for testing and performance evaluation. This data partitioning strategy is commonly employed in machine learning studies to assess model generalization capability on unseen data [8], [9].

Finally, dataset validation was conducted to ensure that all transformed features, generated labels, and data partitions were correctly processed. The validated dataset was subsequently used in the model training and evaluation stages.

### *C. Decision Tree Algorithm*

The Decision Tree algorithm was employed as the primary classification method in this study due to its simplicity, interpretability, and effectiveness in handling structured datasets. Unlike black-box machine learning models, Decision Trees generate explicit classification rules that can be easily interpreted by users and researchers, making them suitable for expert system development and healthcare-related applications [7], [8].

The Decision Tree algorithm was selected because it offers several advantages over more complex machine learning methods for symptom-based medical classification. First, Decision Trees generate explicit and interpretable decision rules, allowing healthcare practitioners and users to understand how a diagnosis is produced. Second, the algorithm requires relatively low computational resources and can efficiently process structured tabular datasets without extensive feature engineering. Third, Decision Trees are well suited for web-based implementation because they provide fast prediction times while maintaining satisfactory classification performance. These characteristics make the algorithm appropriate for preliminary medical screening systems where transparency and computational efficiency are important considerations.

A Decision Tree is a supervised learning algorithm that constructs a hierarchical tree structure consisting of root nodes, internal decision nodes, branches, and leaf nodes. During the training process, the algorithm recursively partitions the dataset into smaller subsets based on the attribute that provides the highest discriminatory power among diagnostic classes. The resulting tree structure represents a series of decision rules used to classify new observations into predefined categories.

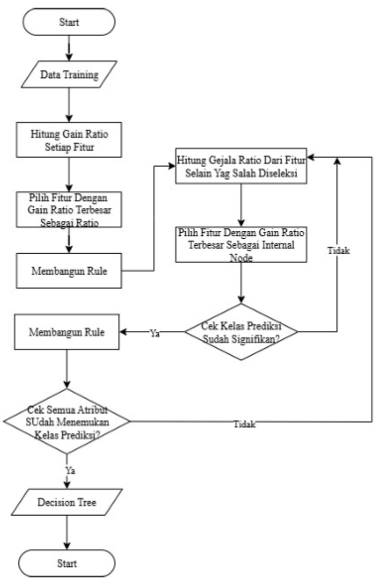


Figure 2. Decision Tree Scheme

Entropy is used to measure the level of uncertainty or heterogeneity of data in each diagnostic class. The lower the entropy value, the more homogeneous the data is considered, thus improving the classification process.

The entropy formula is shown as follows:

$$Entropy(S) = -\sum_{i=1}^{n} p_i \, log_{2\,(p_i)}$$

Information:

- S is a set of datasets
- Pi is the probability of the occurrence of class i
- n is the number of diagnostic classes

The entropy value is then used in the Information Gain calculation process to determine the best attributes in forming a decision tree in the Decision Tree algorithm.

The Information Gain formula is shown as follows:

$$Gain(S,A) = Entropy(S) - \sum_{in \in Values(A)} \frac{|S_{in}|}{|S|} \times Entropy(S_{in})$$

Information:

- A is the attribute being tested
- S is a subset of data based on certain attributes

In this study, the attribute selection process was conducted using the Gain Ratio method to reduce bias against attributes with multiple values. The attribute with the highest Gain Ratio value was selected as the root node in the decision tree structure.

The Gain Ratio formula is shown as follows:

$$GainRatio(A) = \frac{Gain(A)}{SplitInfo(A)}$$

The use of Gain Ratio helps improve the quality of classification because it is able to select the most relevant symptom attributes in determining the diagnosis of eye refractive disorders.

### *D. System Implementation*

The system was developed using the Python programming language with the Flask framework and a MySQL database. The web-based system allows users to perform initial diagnostics through a browser without the need for additional application installation.

The system's main features include:

1. Diagnosis of refractive disorders of the eye
2. Storage of examination history
3. Generate PDF diagnostic report
4. Automatic display of diagnosis results

The system flow begins with the user inputting symptoms. The backend then preprocesses the data and classifies it using a pre-trained machine learning model. The system then generates output in the form of the type of refractive error and a history of the examination, which can be saved and printed. The system is also designed with a simple and responsive interface, making it easier for users to carry out the initial diagnosis process independently through a web-based platform.

In addition to achieving a high level of accuracy, the developed system also demonstrated stable performance in classifying user symptom data. The diagnosis process can be completed in a relatively short time because the Decision Tree algorithm has a low computational complexity compared to other machine learning algorithms. This makes the system optimal for implementation on web-based platforms.

From a user perspective, the system interface is designed to be easily understood by the general public, without requiring technical knowledge of eye health or machine learning. Users simply select their symptoms, and the system automatically performs a classification process and displays the diagnosis along with information regarding the detected refractive error.

Furthermore, the system's examination history storage and PDF report generation feature adds value, allowing users to save diagnostic results for documentation and follow-up consultations with medical professionals. This feature makes the system not only a classification tool but also a digital-based support tool for initial eye health examinations.

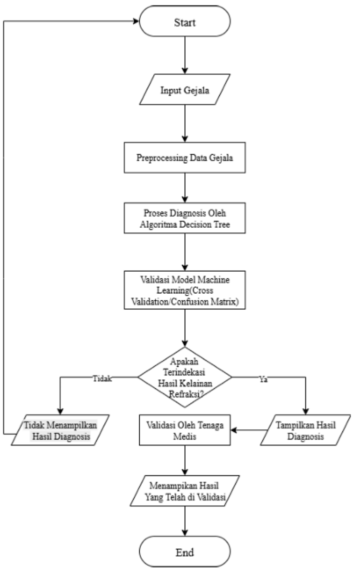


Figure 3. System Schematic

The system developed uses a web-based client-server architecture. Users input symptoms through a browser, then the data is sent to the Flask backend for processing using a Decision Tree model. Once the classification process is complete, the diagnosis results are saved to a MySQL database and displayed to the user via a diagnosis results page.

This architecture allows the system to run lightly, flexibly, and be accessible through various devices that have a browser.

*E. Model Evaluation*

Test results showed that the Decision Tree model produced an accuracy rate of 89.11%. Precision, recall, and F1-score values indicated good classification performance across most diagnosis classes. The model performed best in myopia classification due to its larger data set compared to other classes. The confusion matrix results indicate that the system correctly classified most of the data.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Astigmatisme | 0.00 | 0.00 | 0.00 | 4 |
| Hipermetropi | 0.70 | 0.88 | 0.78 | 8 |
| Miopi | 0.94 | 0.94 | 0.94 | 88 |
| Presbiopi | 0.00 | 0.00 | 0.00 | 1 |
| accuracy | | | 0.89 | 101 |
| macro avg | 0.41 | 0.45 | 0.43 | 101 |
| weighted avg | 0.88 | 0.89 | 0.88 | 101 |

Figure 4. Classification Report of the Decision Tree Model

The classification report indicates that the proposed model achieved an overall accuracy of 89.11%, demonstrating satisfactory performance in classifying refractive eye disorders based on symptom data. Nevertheless, the evaluation metrics reveal noticeable differences among diagnostic classes. The myopia class obtained the highest precision and recall because it constituted the majority of the training data. In contrast, the minority classes, particularly presbyopia and astigmatism, exhibited lower performance due to the limited number of representative training samples.

## III. RESULTS AND DISCUSSION

*A. Result Preprocessing Data*

The dataset used in this study consisted of 505 respondents collected through a structured Google Forms questionnaire. Before the model training process, the dataset underwent preprocessing and was divided into 80% training data (404 instances) and 20% testing data (101 instances) using the hold-out validation method. The dataset distribution across the four diagnostic classes was highly imbalanced, with myopia representing the dominant class and the remaining classes containing considerably fewer observations. Such an imbalanced distribution is expected to influence the learning behavior of the Decision Tree algorithm because the model tends to generate decision rules that favor majority classes. Therefore, model performance was evaluated using multiple metrics, including accuracy, precision, recall, and F1-score, to provide a more comprehensive assessment than overall accuracy alone.

TABLE 1.
DATASET DISTRIBUTION

| Diagnostic Class | Number of Samples | Percentage (%) |
|---|---|---|
| Myopia | 439 | 86.93 |
| Hypermetropia | 39 | 7.72 |
| Astigmatism | 20 | 3.96 |
| Presbyopia | 7 | 1.39 |
| Total | 505 | 100 |

Table 1 shows that the dataset is highly imbalanced. Myopia accounts for 439 out of 505 observations (86.93%), whereas presbyopia is represented by only 7 samples (1.39%). This imbalance is an important characteristic because Decision Tree algorithms tend to generate splitting rules based on the dominant class, resulting in better predictive performance for majority classes than for minority classes. Consequently, the classification performance of minority classes requires further evaluation using precision, recall, and F1-score instead of relying solely on overall accuracy.

TABLE 2.
DATA PREPROCESSING RESULTS

| Preprocessing Stages | Processes Carried Out | Results |
|---|---|---|
| Import Dataset | Importing Google Form result dataset using Pandas library | Dataset successfully loaded into Data Frame |
| Data Cleaning | Cleaning empty data and validating respondent answers | The dataset becomes more consistent |
| Symptom Mapping | Grouping symptoms by diagnostic category | Symptoms are divided into myopia, hypermetropia, astigmatism, and presbyopia. |
| Data Transformation | Converts “Yes” and “No” answers to numeric values 1 and 0. | Dataset ready to be processed by Machine Learning algorithm |
| Labeling Process | Determine the diagnostic label based on the highest symptom score | Each data has a diagnostic label |
| Dataset Splitting | Divide the dataset into training and testing data | 404 training data and 101 testing data |
| Dataset Validation | Ensure the dataset does not contain errors or empty data. | The dataset is valid and ready to use |

Based on the preprocessing results, the dataset was successfully transformed into a structured numerical representation suitable for machine learning classification. Binary encoding of symptom responses simplified the learning process by converting categorical questionnaire data into numerical attributes that could be processed efficiently by the Decision Tree algorithm. In addition, the preprocessing stage improved data consistency through validation, cleaning, and standardized labeling, thereby reducing data redundancy and minimizing potential inconsistencies during model training.

Furthermore, the preprocessing analysis revealed that the dataset was dominated by myopia cases, whereas the remaining diagnostic categories contained substantially fewer observations. This class imbalance is an important characteristic of the dataset because it directly affects the learning process of the Decision Tree algorithm. Majority classes contribute more frequently to node splitting decisions, while minority classes provide fewer representative patterns for rule generation. Consequently, although the model is expected to achieve high overall accuracy, predictive performance for minority classes may be relatively lower. This phenomenon is further analyzed in the model evaluation and discussion sections.

### *B. Decision Tree Model Training*

The Decision Tree model was trained using 404 training instances that had undergone preprocessing and feature transformation. During the training phase, the algorithm recursively selected the most informative symptom attributes based on the Information Gain criterion to construct hierarchical decision rules. Each internal node represents a symptom attribute, while each leaf node corresponds to one of the four diagnostic classes, namely myopia, hypermetropia, astigmatism, and presbyopia.

The generated Decision Tree consists of decision nodes representing symptom attributes and leaf nodes representing the predicted diagnostic classes. Attributes with higher discriminatory capability are positioned closer to the root node because they contribute more effectively to reducing dataset uncertainty through the Information Gain criterion. As a result, the model produces transparent decision rules that allow each diagnostic prediction to be traced systematically from the root node to the corresponding leaf node. This interpretable structure is particularly valuable in healthcare applications because it enables researchers and healthcare practitioners to understand and validate the reasoning behind each diagnosis.

The hyperparameter configuration was selected to balance predictive performance and model simplicity. The entropy criterion was used to maximize information gain during node splitting, while limiting the maximum tree depth to five levels helped reduce model complexity and minimize the possibility of overfitting. Furthermore, a fixed random state ensured that the experimental results were reproducible throughout the training process.

From a computational perspective, the Decision Tree algorithm is computationally efficient because each prediction only requires traversal from the root node to a leaf node. Consequently, the model can generate diagnostic predictions rapidly without demanding extensive computational resources. This efficiency, combined with the model's interpretability, makes the proposed approach suitable for implementation in real-time web-based healthcare applications.

C. Model Evaluation

The proposed Decision Tree model was evaluated using a comprehensive set of classification performance metrics. Since the dataset exhibits a significant class imbalance, relying solely on overall accuracy may lead to misleading conclusions. Therefore, precision, recall, and F1-score were also employed to evaluate the model's capability in correctly identifying each diagnostic class. Furthermore, confusion matrix analysis was conducted to investigate the distribution of correct and incorrect predictions across all classes, providing a more detailed assessment of the classifier's behavior.

Model evaluation was conducted using a confusion matrix together with accuracy, precision, recall, and F1-score to provide a comprehensive assessment of classification performance. The experimental results showed that the proposed Decision Tree model achieved an overall accuracy of 89.11% on the testing dataset. This result indicates that the model is capable of correctly classifying the majority of respondents based on symptom data. However, because the dataset is highly imbalanced, overall accuracy alone is insufficient to represent the true classification capability of the model across all diagnostic categories. Therefore, additional evaluation metrics were analyzed to provide a more comprehensive understanding of the classifier's performance for each diagnostic class.

The superior classification performance achieved for the myopia class is closely related to its dominance within the training dataset. A larger number of training samples enables the Decision Tree algorithm to identify more representative symptom patterns and generate more reliable decision rules. Consequently, the model obtained higher precision, recall, and F1-score values for myopia compared with the minority diagnostic classes.

In contrast, lower performance was observed for astigmatism and presbyopia classifications, both of which obtained an F1-score of 0.00. This limitation is primarily attributed to the extremely small number of available samples in these diagnostic classes, resulting in insufficient representative patterns during the training process. Consequently, the Decision Tree algorithm was less capable of generating reliable decision rules for minority classes, leading to frequent misclassification. This finding confirms that class imbalance remains one of the major challenges affecting symptom-based medical classification.

Although the obtained accuracy indicates promising overall performance, the macro-average F1-score of 0.43 suggests that classification effectiveness was not equally distributed across all diagnostic categories. This result demonstrates that overall accuracy alone cannot fully represent the performance of machine learning models when applied to imbalanced medical datasets. Therefore, future studies should consider collecting additional data and applying class-balancing techniques, such as Synthetic Minority Over-sampling Technique (SMOTE), cost-sensitive learning, or ensemble-based approaches, to improve classification performance for underrepresented classes while preserving model interpretability.

The confusion matrix demonstrates that most prediction errors occurred between the myopia and hypermetropia classes, indicating that several symptom characteristics overlap between these refractive eye disorders. Nevertheless, the majority of myopia cases were classified correctly, confirming the capability of the Decision Tree algorithm to capture dominant symptom patterns effectively. The confusion matrix also confirms that prediction errors occurred more frequently in minority classes, which is consistent with the imbalanced distribution of the dataset.

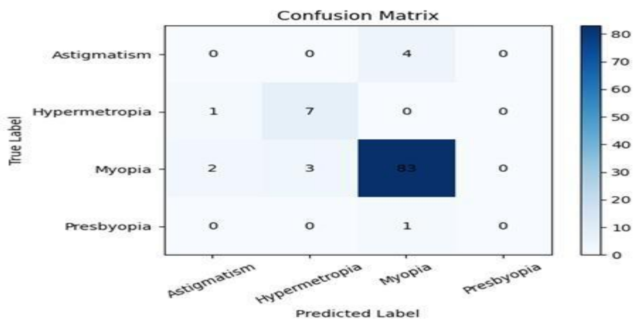


Figure 5. Confusion Matrix Model of the Decision Tree Model

Although the model achieved a relatively high overall accuracy, this metric should be interpreted carefully because the dataset is highly imbalanced. High accuracy may primarily reflect the model's ability to classify the dominant class rather than its effectiveness in recognizing minority classes. Therefore, precision, recall, and F1-score provide a more representative evaluation of model performance for medical diagnostic applications.

Compared with previous Decision Tree-based medical diagnosis studies, the proposed model demonstrates competitive predictive performance while maintaining high interpretability. Unlike black-box machine learning algorithms, every diagnostic prediction generated by the Decision Tree can be traced through explicit decision rules, making the model more transparent and suitable for healthcare decision-support systems.

From a computational perspective, the Decision Tree algorithm performs efficiently because each prediction only requires traversal from the root node to a leaf node. Consequently, the proposed model can generate diagnostic results rapidly while maintaining low computational complexity, making it appropriate for real-time implementation in web-based expert systems.

D. Implementation of Web-Based Systems

The system was successfully implemented as a web-based application using Flask. Users can perform a diagnosis by selecting their symptoms from the website.

After the classification process is complete, the system automatically displays the diagnosis results along with information on the type of refractive error detected. The system also provides a feature for storing examination history and generating diagnostic reports in PDF format.

The web-based system was successfully implemented using the Flask framework with an HTML, CSS, and Bootstrap-based interface. The system implementation allows users to perform self-diagnosis through a browser without the need for additional application installation.

The system interface is designed to be simple and responsive, making it easy for users to understand the diagnostic process. The system can also store user test results in a MySQL database to support more structured and efficient management of diagnostic history.

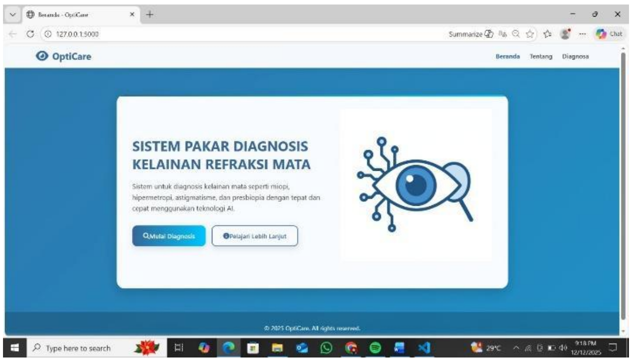


Figure 6. Landing Page View

The landing page serves as the main entry point of the proposed web-based expert system. It provides general information about the purpose of the application and guides users to initiate the preliminary eye health screening process. The interface was designed with a clean and responsive layout to improve usability across different devices and web browsers. Figure 6 illustrates the landing page of the developed system, which functions as the initial interaction between users and the expert system before proceeding to symptom selection and diagnostic analysis.

The diagnosis page allows users to select visual symptoms experienced through an interactive checklist. Each selected symptom is converted into numerical input that is processed by the trained Decision Tree model to generate a preliminary diagnosis. The interface is intentionally designed to simplify the symptom input process while minimizing user errors during data entry.

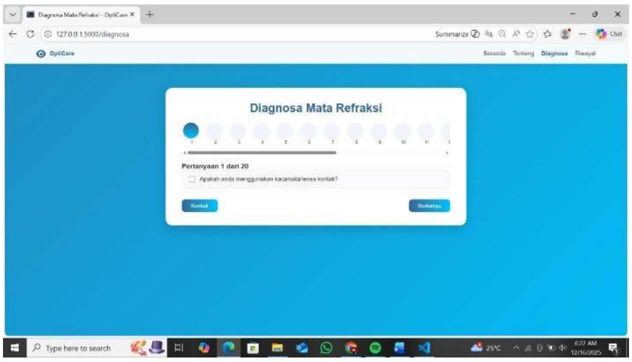


Figure 7. Diagnosis Page View

After the classification process is completed, the system presents the predicted refractive eye disorder together with supporting diagnostic information. The diagnosis result page also provides options to save examination history and generate a PDF report, allowing users to retain the screening results for future reference or consultation with healthcare professionals.

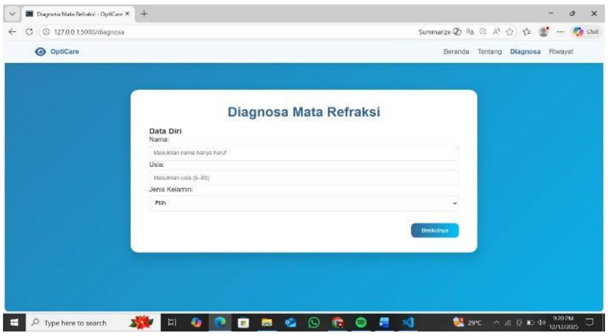


Figure 8. Display of Diagnosis Results

*E. System Testing (Black Box Testing)*

System functionality testing was conducted using the Black Box Testing method, which evaluates the suitability of system output to given input. Test results for the system's 10 main features are presented in Table 1. Based on the results of the tests carried out, all features in the system ran properly and produced outputs that met the specified requirements.

Furthermore, no critical errors were identified during the testing process, indicating that the developed system is sufficiently stable for preliminary deployment and practical use as a web-based diagnostic support tool. The testing results also confirmed that the application was able to process user inputs, perform diagnostic classification, and generate outputs consistently according to the expected functionality. In addition, the system was capable of handling user interactions efficiently and responding appropriately to various input scenarios. These findings demonstrate that the developed application provides a reliable platform for supporting preliminary diagnosis activities and can be utilized as an accessible tool for symptom-based eye health assessment.

TABLE 3.
SYSTEM TESTING

| No | Tested Features | Given Input | Expected results | Status |
|---|---|---|---|---|
| 1 | Home View | Open the main page | The home page displays well | Passed |
| 2 | Diagnosis Form | Select the symptoms experienced | The system receives symptom input. | Passed |
| 3 | Diagnostic Process | Press the diagnosis button | The system processes symptom data | Passed |
| 4 | Diagnostic Results | User symptom data | The system displays the diagnosis results | Passed |
| 5 | Inspection History | Open history page | Diagnostic history data is displayed | Passed |
| 6 | Clear History | Press the delete button | History data successfully deleted | Passed |
| 7 | Print PDF | Press the print PDF button | The system generates PDF files | Passed |
| 8 | Input Validation | Not selecting symptoms | The system processes input validation | Passed |
| 9 | Results View | Opening the results page | The results page displays properly. | Passed |
| 10 | Menu Navigation | Selecting a menu on the website | The system switches pages correctly | Passed |

### *F. Discussion*

The experimental results demonstrate that the Decision Tree algorithm can effectively identify symptom patterns associated with refractive eye disorders. The achieved accuracy of 89.11% indicates that symptom-based classification can be utilized as a preliminary diagnostic approach for eye health screening.

The obtained accuracy of 89.11% indicates that the Decision Tree algorithm is capable of learning meaningful relationships between visual symptoms and refractive eye disorders. This result demonstrates that symptom-based classification can provide an effective preliminary screening approach without requiring specialized ophthalmic equipment. Furthermore, the transparent structure of the Decision Tree allows each diagnostic decision to be interpreted through explicit decision rules, making the proposed approach suitable for healthcare applications that require explainable artificial intelligence.

Although the overall accuracy is relatively high, the confusion matrix and classification report indicate that predictive performance differs substantially among diagnostic classes. This finding confirms that overall accuracy alone is insufficient for evaluating medical classification models, particularly when class distributions are highly imbalanced. Therefore, precision, recall, and F1-score should be considered jointly to obtain a more reliable assessment of the classifier's performance.

One of the primary advantages of the Decision Tree algorithm is its high interpretability. Unlike black-box machine learning models, Decision Trees generate explicit decision rules that allow researchers and healthcare practitioners to trace every diagnostic prediction systematically. This explainable decision-making process is particularly important in healthcare because diagnostic recommendations should be transparent, understandable, and clinically justifiable. Therefore, the proposed model not only provides satisfactory predictive performance but also supports trustworthy clinical decision support.

However, the confusion matrix analysis revealed that classification performance was considerably higher for myopia than for the remaining diagnostic categories. This result is primarily associated with the imbalanced distribution of the dataset, where myopia constituted the majority of training samples. A larger number of representative observations enabled the Decision Tree algorithm to generate more reliable decision rules for the dominant class, whereas the limited number of astigmatism, hypermetropia, and presbyopia samples reduced the model's ability to learn representative symptom patterns. Consequently, minority classes experienced lower recall and F1-score values despite the satisfactory overall accuracy.

Compared with the study by Setiani et al. [16], which applied the C4.5 algorithm for diabetes prediction, the proposed model achieved comparable classification performance while providing an implementation specifically designed for symptom-based refractive eye disorder screening. In addition to providing satisfactory predictive accuracy, this study integrates the trained Decision Tree model into a web-based expert system that supports symptom-based screening, diagnostic history management, and automated report generation. These features enhance the practical applicability of the proposed approach for preliminary eye health screening in environments with limited access to ophthalmology services.

Despite these promising results, several limitations should be acknowledged. The primary limitation of this study is the highly imbalanced dataset, which affected the model's ability to classify minority diagnostic categories accurately. Future research should therefore investigate data balancing techniques such as Synthetic Minority Over-sampling Technique (SMOTE), cost-sensitive learning, or ensemble-based Decision Tree methods. In addition, comparative evaluation using other machine learning algorithms, including Random Forest, Support Vector Machine, and Gradient Boosting, would provide a broader understanding of the strengths and limitations of the proposed approach.

## IV. CONCLUSION

This study successfully developed and evaluated a web-based expert system for the preliminary diagnosis of refractive eye disorders using the Decision Tree algorithm. The proposed model effectively classified four categories of refractive eye disorders—myopia, hypermetropia, astigmatism, and presbyopia—based on symptom data collected through an online questionnaire. The study demonstrates that Decision Tree is an interpretable machine learning approach capable of supporting preliminary medical screening through transparent decision rules.

The experimental evaluation showed that the proposed Decision Tree model achieved an overall accuracy of 89.11%, indicating satisfactory performance for symptom-based preliminary eye health screening. In addition to achieving competitive predictive performance, the model provides transparent decision-making that enables each diagnostic result to be interpreted through explicit classification rules. These characteristics make the proposed system suitable as a decision-support tool for preliminary eye health assessment rather than a replacement for professional ophthalmological examination.

Despite the promising results, this study has several limitations. The highly imbalanced dataset reduced classification performance for minority diagnostic categories, particularly astigmatism and presbyopia. Furthermore, the diagnostic labels were derived from questionnaire-based symptom data and were not clinically validated by ophthalmologists. Therefore, future research should involve larger and more balanced datasets, incorporate data balancing techniques such as SMOTE, perform external clinical validation, and compare the proposed model with other machine learning algorithms to further improve classification performance and model generalization.

Overall, this study demonstrates that integrating an interpretable Decision Tree model into a web-based expert system is a feasible approach for supporting preliminary refractive eye disorder screening. The findings contribute to the development of accessible and explainable intelligent healthcare systems that can assist early detection, particularly in regions with limited access to ophthalmology services.

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