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EARLY DIAGNOSIS OF EYE DISEASE USING AN EXPERT SYSTEM-BASED CHATBOT

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ABSTRACT
Chatbots have emerged as popular tools across various domains, including expert systems for disease diagnosis. This research aims to develop a chatbot leveraging the Naive Bayes method within an expert system for diagnosing eye diseases. The Naive Bayes method was chosen for its efficiency in handling data classification and its ability to provide the necessary class probabilities in diagnosis. The resulting chatbot is designed to simplify the diagnosis process for users by providing a user-friendly and easily understandable interface. Evaluation of the system demonstrated an 87% accuracy rate in initial diagnoses when compared against specialist evaluations. Additionally, the User Acceptance Test revealed a high acceptance rate, with an average score of 84.75%, indicating strong user satisfaction with the system's performance and ease of use. These findings suggest that deploying a chatbot with the Naive Bayes method in an expert system for diagnosing eye diseases has the potential to serve as a valuable platform in supporting medical practitioners in diagnosing eye diseases more efficiently and accurately.

Keywords: chatbot; early diagnosis; eye disease; expert system; naïve bayes; optimization

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INTRODUCTION

The eye is an essential organ in human life as it serves as the primary tool in visual perception, enabling individuals to interact effectively with their surrounding environment (Li et al., 2022). A good visual ability is crucial for engaging in various daily activities, ranging from work to recreational pursuits. Additionally, the eye plays a vital role in maintaining body balance and coordinating movements. Therefore, maintaining eye health is crucial for ensuring optimal quality of life for individuals (Ramke et al., 2022; Williams et al., 2020). Early diagnosis of eye diseases holds significant importance in preventing serious complications and preserving an individual's visual (Alkatan & Al-Essa, 2019; Cicinelli et al., 2020; Tan et al., 2023; Verjee et al., 2020). However, there are several challenges in conducting timely and accurate eye examinations, such as limited access to eye specialists and the time required to obtain a precise diagnosis.

Expert systems have been extensively developed in various fields requiring expertise and early diagnosis of a problem, including conducting initial diagnoses of eye diseases (Muntean et al., 2023; Siddique et al., 2022)(Gama & Putri, 2020). Expert systems operate by analyzing problems based on provided data, utilizing rules and structured knowledge bases to deduce relevant information, akin to how a human expert would solve problems (Kurniawan et al., 2019; Mazhar et al., 2022; Poeschl et al., 2017; Siek & Urian, 2021). The knowledge base in expert systems contains data on eye diseases and their symptoms, while the inference engine conducts searches for symptoms based on established rules to establish a diagnosis (Dutta & Wilson, 2021; Gholamzadeh et al., 2023).

However, developing conventional expert systems often requires a high level of technical expertise and considerable time (Soetanto et al., 2024)(Gama et al., 2022). This process involves knowledge modeling and implementing complex rules, coupled with the provision of intricate interfaces for user interaction. Undoubtedly, this poses a barrier to the development of effective and efficient expert systems. In recent decades, advancements in information and communication technology have transformed the paradigm of enhancing accessibility and service efficiency. One prominent innovation is the utilization of chatbots, which are computer programs designed to interact with users through natural language conversations (de Pennington et al., 2021). Chatbots function as assistants capable of communicating with users via text messages, serving as virtual companions integrated into applications or text messaging platforms.

This research aims to develop an expert system using a different approach, namely chatbot-based. Several previous studies have explored the use of chatbots for automated question-and-answer processes (Alturaiki et al., 2022; Villegas-Ch et al., 2020). With the expert system approach through chatbots, system development becomes simpler without requiring the creation of complex applications or websites as interfaces (Fatani & Banjar, 2024). The combination of the reliability of the naive Bayes expert system in diagnosing diseases with the capabilities of chatbots in interaction forms a more effective and efficient system development(Gama & Wardhiana, 2023). By leveraging the advantages of chatbots in accessibility and intuitive user interaction, it is hoped that a platform can be created that allows individuals to perform initial diagnosis of eye diseases quickly and accurately. Based on the background above, this research aims to further explore the development of a Chatbot-based expert system for early diagnosis of eye diseases using the Naïve Bayes Method. The development of this chatbot-based expert system aims to create a platform for obtaining more efficient diagnoses and facilitating user interaction with the system.

METHOD

The expert system developed in this study utilizes the Telegram engine as the user interface. Telegram was chosen due to its easily implementable API. Another reason for choosing Telegram is that it has been downloaded approximately 80 million times in Indonesia (World Population Review, 2024). This expert system follows a repetitive flow, where interactions between users and the system occur repeatedly to draw conclusions based on provided information. The process of the chatbot-based expert system for the initial diagnosis of eye diseases is outlined in detail in the system overview.

A. System Overview

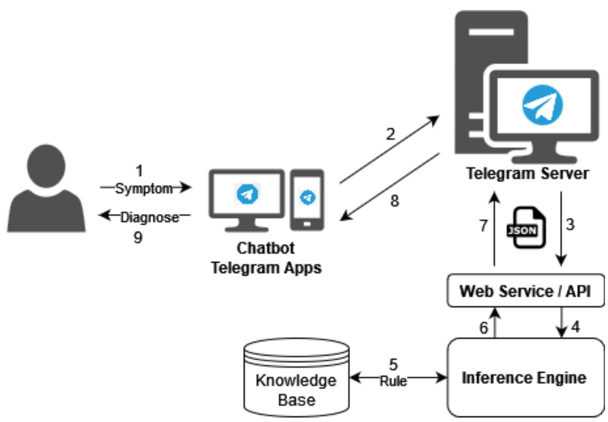

Figure 1. Chatbot Expert System Overview

Figure 1 depicts the model developed for the chatbot-based expert system for early diagnosis of eye diseases. In Step 1, users send text messages containing symptom data through the Telegram instant messaging application on computers or smartphones. Step 2 illustrates that the text messages sent by users are forwarded to the Telegram server. There, the text messages undergo processing, transforming into JSON format with additional information such as sender identifier, message content, message delivery time, and so forth. Step 3 indicates that the text message data in JSON format is forwarded to the system. The system parses the received JSON data to extract message content, user identification, and other details in Step 4. The extracted message content is then passed to the inference engine for the tracing or inference process in Step 5. This process involves matching the message content with the knowledge base to generate a response corresponding to the user's message. Step 6 displays the response successfully obtained by the system, which is treated as the output ready to be sent back to the user. In Step 7, the expert system sends the output, in the form of a response, to the user through the Telegram server using the user identifier. The response is then forwarded to the user's device in Step 8. Step 9 presents the response successfully displayed to the user, consisting of an initial diagnosis through the Telegram instant messaging application. This process repeats, forming a conversation between the user and the expert system aimed at providing solutions to the user's problem.

B. Knowledge Base

The fuel for the expert system developed in this research is the knowledge base. The knowledge base in this study consists of pairs of diseases and symptoms related to eye diseases. The details of the eye disease knowledge base are elaborated in Table 1 below. This table provides comprehensive information about various eye diseases and their associated symptoms, serving as the primary foundation for the diagnostic and decision-making processes of the developed expert system.

Table 1.
Rule Base

Diseases	Diseases Weight	Symptoms	Weight
Glaucoma (P01)	80	Eyes feel hard (G01)	20
		Cloudy eye lens (G19)	10
		Blurred vision (G17)	20
		Red eyes (G02)	5
		Watery eyes (G03)	5
		Pain in the eyeball (G04)	20
		Headache (G05)	20
Conjunctivitis Virus (P02)	55	Red eyes (G02)	30
		Eyes irritated (G06)	5
		Eyes feel hot (G10)	5
		Eyes feel sore (G48)	10
		Swollen eyelids (G08)	20
		Watery eyes (G03)	30
Conjunctivitis Allergen (P03)	65	Red eyes (G02)	20
		Eyes irritated (G06)	10
		Eyes feel itchy (G12)	20
		Mucous eye discharge (G15)	10
		Swollen eyelids (G08)	10
		Watery eyes (G03)	30
Cataract (P04)	90	Blurred vision (G17)	40
		Seeing double in one eye (G18)	5
		Cloudy eye lens (G19)	30
		Suffering from diabetes (G20)	5
		Sensitive to light (G16)	10
		White spots on pupils (G21)	10

Hypermetropia (P05)	70	Not clear to see at close distances (G22)	50
		Headache (G05)	15
		Watery eyes (G03)	15
		Eyes feel hurt (G11)	15
		Get sleepy quickly while reading (G23)	5
Myopia (P06)	70	Not clear to see long distances (G24)	50
		Headache (G05)	15
		Watery eyes (G03)	15
		Eyes feel hurt (G11)	15
		Get sleepy quickly while reading (G23)	5
Astigmatism (P07)	50	Not clear to see long distances (G24)	20
		Seeing objects as uneven (G25)	10
		Things seem to sway (G26)	10
		Headache (G05)	20
		Get sleepy quickly while reading (G23)	10
		Watery eyes (G03)	15
		Eyes feel hurt (G11)	15
Pterigium (P08)	35	Red eyes (G02)	30
		Eyes irritated (G06)	15
		Blurred vision (G17)	5
		There is a triangular lump (G27)	50
Retinal Ablasio (P09)	30	Seeing flying objects (floaters) (G28)	30
		Seeing strong flashes of light (photopsia) (G29)	20
		Blurred vision (G17)	25
		Vision as if covered by a curtain (G30)	25
Xerophthalmia (P10)	15	Itchy eyes (G12)	30
		Eye stinging (G34)	15
		Sensitive to light (G16)	25
		Pale lymph nodes and conjunctiva (G35)	30
Uveitis (P11)	18	Red eyes (G02)	25
		Eye pain (G48)	10
		Watery eyes (G03)	10
		Blurred vision (G17)	20
		Pus at the edge of the cornea (G38)	10
		Red at the edge of the cornea (G39)	30
Keratitis (P12)	14	Eye pain (G48)	20
		Light sensitive (G16)	20
		Eyes are difficult to open (G52)	20
		Blurred vision (G17)	10
		Red at the edge of the cornea (G39)	20
		Red eyes (G02)	10
Hypertensive Retinopathy (P13)	23	Blurred vision (G17)	10
		Eyes appear white/pale (G42)	10
		Glass body hemorrhage (G43)	10
		Hypertensive disease factors (G44)	70
Dacryocystitis (P14)	13	Red eyes (G02)	15
		Watery eyes (G03)	10
		Swollen eyelids (G08)	50
		Fever (G49)	5
		Discharge (pus) when pressing on the eyelid (G47)	20

The knowledge base presented in Table 1 above will serve as rules for the inference engine in the developed expert system. These rule-based structures are then formatted into a web service to be accessed and processed by the Telegram Chatbot. Consequently, the Telegram Chatbot can utilize the information contained within this knowledge base to provide responses or initial diagnoses based on symptoms conveyed by the user.

C. Inference Engine

The inference engine processes the input provided by the user as the basis for searching for an appropriate diagnosis. The input received by the system is systematically processed using predefined rules within the knowledge base. This process aims to match the symptoms reported by the user with the symptom patterns available in the knowledge base. Through these steps, the inference engine can generate accurate and relevant initial diagnoses related to the user's eye health condition.

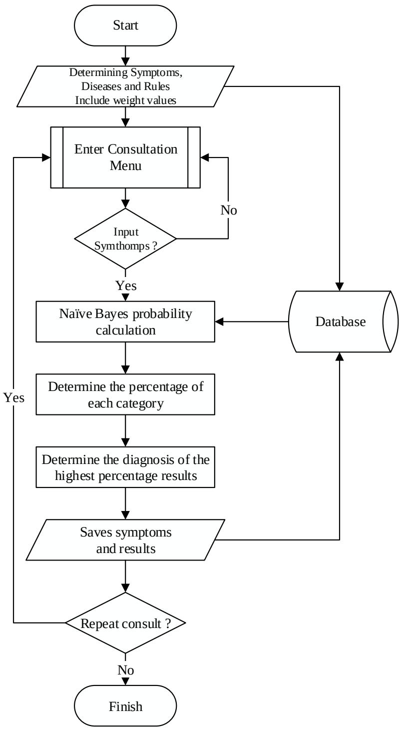

Figure 2. Inference Process

The inference process flowchart was created based on previous research on the Naive Bayes expert system. Figure 2 illustrates the steps of the inference process by conducting consultations, where users respond to symptoms presented by the system. The answered symptoms are then stored in the database and their probabilities are calculated using the Naive Bayes method. The calculation results will indicate the initial diagnosis of eye diseases that users may have based on the symptoms reported.

D. Naive Bayes

Naïve Bayes was first proposed by the British scientist Thomas Bayes, aiming to predict future probabilities based on past experiences. Naïve Bayes is a method for simple probability classification based on Bayes' Theorem. In Bayes' Theorem, combined with the concept of "Naïve," which means independent attributes. Naïve Bayes calculates the probability of a class based on its attributes and determines the class with the highest probability. The advantage of this classification is that Naïve Bayes only requires a small amount of training data to estimate the parameters needed for classification, namely the mean and variance of the variables. Only the variations of the variables for each class need to be determined because the variables are assumed to be independent, not the entire covariance matrix. The calculation of Naïve Bayes is outlined in Formula 1:

$$p(K|G) = \frac{p(G|K)\ .\ p(K)}{p(G|K)} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (1)$$

Description:

G= Evidence observed

K= Condition being evaluated
P(G)= Probability of observing the evidence G
P(K)= Prior probability of the condition K
P(K/G)= Posterior probability of K given G
P(G/K)= Likelihood of G when G is present
In this formula, P(K/G) known as the posterior probability, calculates the likelihood of a class (K) such as a specific eye disease, occurring given the observed evidence or symptom (G). The term P (G/K) called the likelihood, represents the probability of observing the symptom (G) when the class (K) is true, essentially capturing how strongly the evidence is associated with the class. P(K) the prior probability, quantifies how frequently the class (K) appears in the population or dataset without considering specific evidence. The denominato P(G) serves as the evidence probability, which ensures proper normalization of the probabilities. It is the total probability of observing the symptom G, accounting for all possible classes by summing P (G/K). P(K) across each class. Together, this formula combines prior knowledge P(K) and the observed evidence (G) to compute a well-calibrated posterior probability P (K/G), enabling predictions that are grounded in both data and statistical reasoning.

E. Chatbot as Interface
Instant messaging is a chat communication facility used by Internet users. By using this facility, users can communicate by sending text messages or files, as well as making calls with other users. In addition to interacting with other users, they can also utilize the chatbot feature. A chatbot is a program capable of communication and conversation using natural language. Chatbots can be implemented in various fields such as commercial entertainment, education, and healthcare. Chatbots generate responses and send them back to users. Chatbots are supported by machines with rule-based systems or artificial intelligence (AI) that interact with users through text-based interface messages (Chow et al., 2024). One platform that features chatbots is Telegram. In Telegram, there is a feature that can be utilized for the development of expert systems, namely Telegram Bot. Bots can be designed to interact with users, such as by sending messages, engaging in conversations, and so on. In this research, the bot will be developed to interact with users and to deduce initial diagnoses of eye diseases based on Naïve Bayes calculations.

RESULT

A. Implementation on Chatbot
The system begins by searching for the "PenyakitMata_bot" Bot using the search feature available in the Telegram application. Once the appropriate Bot is found, users initiate a conversation by tapping the "start" button displayed on the screen, as shown in Figure 3.

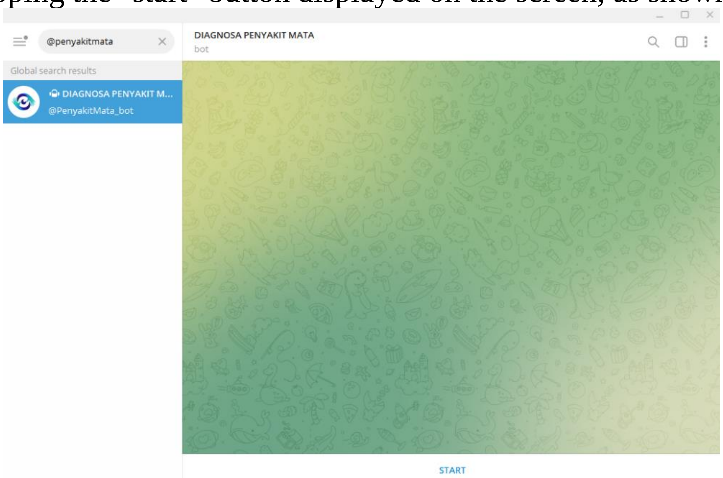

Figure 3. Bot Search on Telegram Apps.

The "PenyakitMata_bot" Bot then provides users with the option to "Diagnose Disease" or view "My Diagnosis History" as shown in Figure 4. If users do not have a diagnosis history yet, they are required to select the "Diagnose Disease" option first.

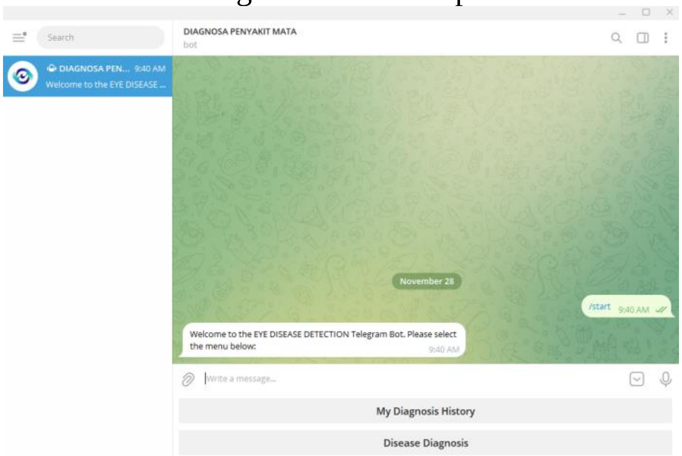

Figure 4. Selection of features in Bot

The diagnosis process begins with the bot requesting users to fill personal information according to the given format, such as name, age, gender, and other relevant details. Once the personal data is provided, the bot initiates the consultation process by displaying a series of symptoms that may be associated with eye diseases as shown in Figure 5.

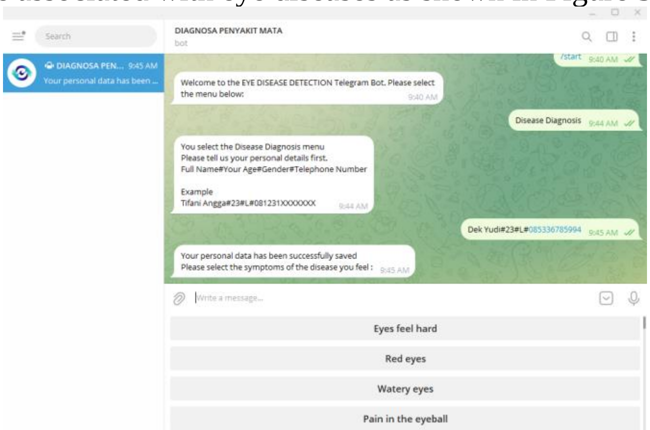

Figure 5. Consultation process

Figure 5 illustrates that users can select the symptoms they are experiencing based on their current condition. Each time a symptom is selected, The Bot will ask questions to ascertain whether any other symptoms are being experienced. If there are, users can choose the "Yes" option, and The Bot will then display the symptom options again, which the user can select based on their experience.

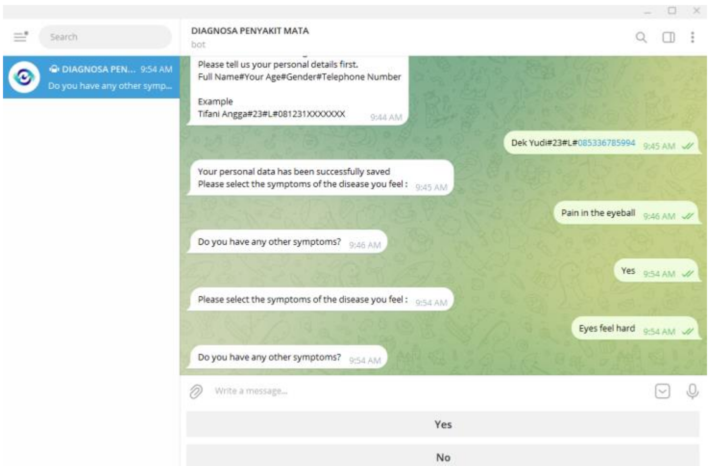

Figure 6. Inference Process

However, if there are no relevant symptoms left, users can choose the "No" option as in Figure 6 above. The Bot then proceed to Naïve Bayes algorithm, calculate highest possible disease. from the front-end side the bot terminates the diagnosis session and summarize the consultation process, displaying the diagnosis results of eye diseases based on the symptoms selected by the user. Consequently, users can easily and quickly diagnose eye diseases through the "PenyakitMata_bot" Bot in a few simple and efficient steps.

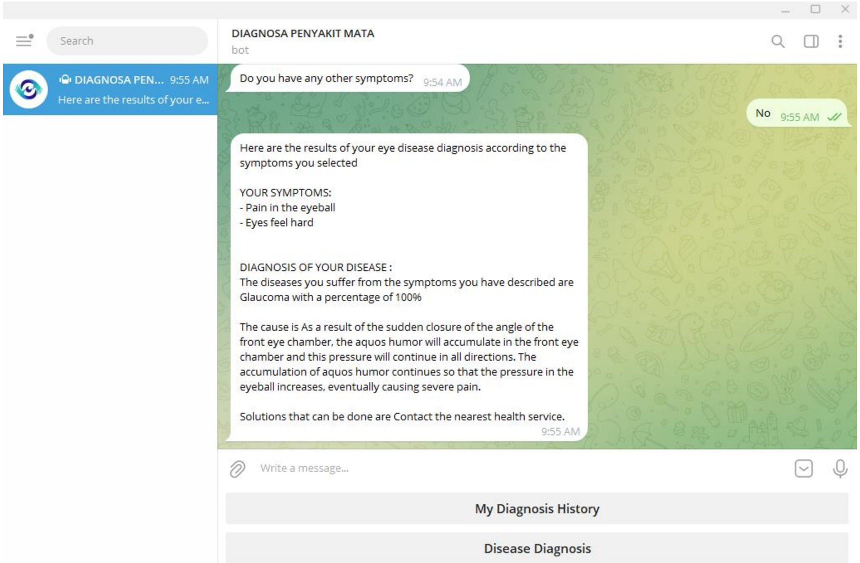

Figure 7. The Diagnosis Results

The outcome generated by this chatbot-based expert system is depicted in Figure 7, consisting of an initial diagnosis of eye diseases. This initial diagnosis includes an explanation of potential eye diseases experienced by the user, along with their causes and initial solutions. Moreover, this outcome can assist specialist doctors in determining subsequent actions.

B. Implementation of Naïve Bayes Method

The system collects all the symptoms that the user has selected, identifies the disease associated with those symptoms, and calculates the probability of the disease based on the weight and score assigned to each symptom. The code follows an approach adapted from the principles of Naive Bayes:

Program Journal

```
$listSymptomId = [];
$diseaseId = [];
$diseaseSymptom = [];
$diagnose = Diagnose::where('chat_id' , $userId)->orderBy('created_at' , 'DESC')->first();
$SymptomDiagnose = [];
$diseaseDiagnose = [];
```

Variables are initialized to store symptom IDs, disease IDs, and the relationships between diseases and symptoms. Subsequently, the latest diagnosis associated with the specific chat ID is retrieved from the database to ensure accurate and context-aware processing of medical information.

Program Journal

```
foreach (json_decode($diagnose->record_symptom) as $symptomName) {
$symptom = Symptom::where('symptom_name' , $symptomName)->first();
$ diseaseSymptom = diseaseSymptom::where('symptom_id' , $symptom->id)->get();
$symptomDiagnose[] = $symptom->symptom_name;
$numerator = 0;
$denominator = 0;
```

The system iterates through each symptom selected by the user, searching for related symptoms and diseases in the database. Variables are then initialized to calculate the numerator and denominator in the probability formula, setting the stage for accurate diagnostic computations.

Program Journal
foreach ($diseaseSymptom as $data) {$denominator += $data-> weight * $data->disease->score;} foreach ($diseaseSymptom as $data) {$numerator = $data->weight * $data->disease->score; $ratio = round($numerator / $denominator , 3);
The system calculates the denominator by aggregating the total weights of all diseases associated with the symptoms. It then computes the numerator for each disease linked to the symptoms, determining the relative probability of each disease.
Program Journal

if (!empty($diseaseDiagnose)) {$diseaseIdArray = array_column($diseaseDiagnose, 'diagnose_id)
if (in_array($data->diagnose->id, $diseaseIdArray)) {foreach ($diseaseDiagnose as $key => $value)
{if($value['diagnose_id] == $data->diagnose->id){$Prob = $value['total_prob']; $value['total_prob'] = $Prob + $ratio; $value[percentage] = $value['total_prob'] * 100;

The system accumulates probabilities for diseases that are already recorded, effectively calculating the total probability of each disease based on all symptoms input by the user.
Program Journal
}}}else{$diagnosaPenyakit[] = ['id_penyakit' => $data->penyakit->id, 'total_probabilitas' => $totalBagi, 'persentase' => $totalBagi * 100,];}}

If a disease is not already recorded, it is added to an array with its initial probability value, ensuring all potential diseases and their probabilities are tracked. This is the core of the calculation process that adopts the Naive Bayes principle, assuming that symptoms are independent of each other and their contribution to the disease is calculated separately and then accumulated to get the final probability picture. To explain the Naïve Bayes calculation algorithm, it can be simulated by manual calculation using the Naïve Bayes formula. This can be exemplified in a case where the user selects the symptom "Eyes feel hard" (G04) as shown below.

Probability of Glaucoma (P01|G04):

$$p(P01|G04) = \frac{p(G04|P01) * p(P01)}{\begin{array}{c} p(G04|P01) * p(P01) + p(G04|P02) * p(P02) + p(G04|P03) * p(P03) + \\ p(G04|P04) * p(P04) + p(G04|P05) * p(P05) + p(G04|P06) * p(P06) + \\ p(G04|P07) * p(P07) + p(G04|P08) * p(P08) + p(G04|P09) * p(P09) + \\ p(G04|P10) * p(P10) + p(G04|P11) * p(P11) + p(G04|P12) * p(P12) + \\ p(G04|P13) * p(P13) + p(G04|P14) * p(P14) + p(G04|P15) * p(P15) + \\ p(G04|P16) * p(P16) + p(G04|P17) * p(P17) + p(G04|P18) * p(P18) + \\ p(G04|P19) * p(P19) + p(G04|P20) * p(P20) + p(G04|P21) * p(P21) + \\ p(G04|P22) * p(P22) + p(G04|P23) * p(P23) + p(G04|P24) * p(P24) + \\ p(G04|P25) * p(P25) \end{array}}$$

$$p(P01|G04) = \frac{p(20) * p(80)}{\begin{array}{c} p(20) * p(80) + p(0) * p(0) + p(0) * p(0) + p(0) * p(0) + \\ p(0) * p(0) + p(0) * p(0) + p(0) * p(0) + p(0) * p(0) + \\ p(0) * p(0) + p(0) * p(0) + p(0) * p(0) + p(0) * p(0) + \\ p(0) * p(0) + p(0) * p(0) + p(0) * p(0) + p(0) * p(0) + \\ p(0) * p(0) + p(0) * p(0) + p(0) * p(0) + p(0) * p(0) + \\ p(0) * p(0) + p(0) * p(0) + p(0) * p(0) + p(0) * p(0) + \\ p(0) * p(0) \end{array}}$$

$$p(P01|G04) = \frac{1600}{1600}$$

$$p(P01|G04) = 1$$

In the case of this symptom, it only corresponds to one eye disease, thus according to the system, the user is likely suffering from Glaucoma with a probability of 1 or 100%. Since the system provides an initial diagnosis, other diseases that approach the highest value can be used as additional references for the expert to determine the next course of action.

D. Validation Testing

In this testing process, the diagnostic history of users who have performed an initial diagnosis is stored in the database. The accuracy of this diagnostic history is then evaluated by comparing it with the results provided by a specialist. During this testing, the researcher collaborated with an ophthalmology expert to validate the outcomes of the developed system.

Table 2.
Validation Test Result

No	Symptoms inputted	Expert System Diagnosis Results	Expert Diagnosis Results	Conformity of Diagnosis Results
1	G03, G24, G11	Myopia	Myopia	Sesuai
2	G03, G05, G23, G11, G26	Astigmatism	Astigmatism	Sesuai
3	G04, G17, G03, G02	Glaucoma	Glaucoma	Sesuai
4	G10, G12, G03, G11	Conjunctivis Virus	Conjunctivis Virus	Sesuai
5	G16, G17, G03, G35	Xerophthalmia	Xerophthalmia	Sesuai
6	G03, G05, G02, G24	Myopia	Keratitis	Tidak Sesuai
.	.	.	.	.
.	.	.	.	.
22	G08, G17, G45, G44	Hypertensive Retinopathy	Hypertensive Retinopathy	Sesuai
23	G40, G17, G16, G03	Uveitis	Uveitis	Sesuai

This validation test used 23 diagnostic results permitted by the respondents. The average accuracy value is calculated to determine the diagnostic accuracy of the expert system, alongside forming a conclusion. Based on the testing results, out of 23 diagnostic data entries, 20 were deemed correct or consistent with the expert’s diagnosis, while the remaining 3 were considered inaccurate or inconsistent. The accuracy rate of the expert system’s diagnosis is then calculated using the following formula 2:

$$Accuracy = \frac{N_{correct}}{N_{total}} \times 100\% \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$Accuracy = \frac{20}{23} \times 100\% = 86.9\% = 87\%$$

From this calculation, it can be concluded that the expert system can provide an initial diagnosis with an accuracy level of 87%. However, this accuracy level is not sufficient to definitively confirm that a patient has the eye condition diagnosed by the system. The system serves only as an initial diagnostic tool, and further evaluation by a medical expert or healthcare professional is required to ensure a precise diagnosis and appropriate treatment.

E. User Acceptance Test (UAT) Result

The system testing was conducted using the User Acceptance Test (UAT) method. This test aims to assess the suitability and acceptance of the system by the public. The testing took place after respondents utilized the system for initial consultation of eye disease diagnosis. Respondents were directed to a Google Form containing predefined questions. They then responded by selecting items on a graded scale, ranging from Strongly Disagree (SD) to Strongly Agree (SA). The data was then processed by multiplying each point of response by the predetermined weighting value. "Strongly Disagree" was assigned a weighting value of 1, "Disagree" a value of 2, "Agree" a value of 3, and "Strongly Agree" a value of 4. From the calculation results obtained by multiplying each response by the designated weighting value, the analysis of the UAT testing is presented in Table 4 below. A total of 57 respondents completed the questionnaire, obtained through distribution via social media. The following table presents the results of the User Acceptance Test (UAT).

Table 3.
User Acceptance Test Result

No	Statements	Rating				Weight Rating				Percentage
		SD	D	A	SA	SD	D	A	SA	
1	I am very satisfied with the ease of use of this chatbot-based expert system	0	0	46	11	0	0	135	48	80.26%
2	This expert system's response time to my diagnosis request was quite fast	0	5	25	27	0	10	75	108	84.65%

3	This expert system provides accurate diagnosis results	0	5	32	20	0	10	96	80	81.58%
4	This expert system provides accurate diagnosis results. The information provided by this expert system is easy to understand	0	0	25	32	0	0	75	128	89.03%
5	The language used in the system is easy to understand	0	2	18	37	0	4	54	148	90.35%
6	I am very satisfied with the use of the disease diagnosis feature in this expert system	0	0	33	24	0	0	99	96	85.53%
7	The "My Diagnosis History" feature in this expert system helps me refer back to previous disease diagnoses that have been made	0	2	30	25	0	4	90	100	85.09%
8	You will not experience errors when using this expert system	0	7	28	22	0	14	84	88	81.58%
9	I am satisfied with the experience of using this chatbot-based expert system	0	2	31	24	0	4	93	96	84.65%

Based on the responses from 57 respondents, as shown in Table 3, most respondents answered "Agree" to each given question. This was followed by "Strongly Agree," with a small portion answering "Disagree." After obtaining the values for each question, the next step is to calculate the overall average score using formula 3:

$$\bar{x} = \frac{\sum x}{n} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3)$$

$$\bar{x} = \frac{(80.26\% + 84.65\% + 81.58\% + 89.03\% + 90.35\% + 85.53\% + 85.09\% + 81.58\% + 84.65\%)}{9}$$

$$\bar{x} = 84.75\%$$

Overall, the survey results indicate that this expert system for early eye disease diagnosis received positive feedback from most respondents, achieving an average acceptance rate of 84.75%. The system interface was considered easy to understand, facilitating interaction with the system. Additionally, the system's response to diagnosis requests was deemed sufficiently prompt by the respondents. This indicates that the system can provide quick responses to users' needs in conducting initial diagnosis of eye diseases. Although the satisfaction level was slightly lower, respondents still felt that this expert system provided accurate initial diagnoses. However, this suggests potential for improving the accuracy of the expert system's diagnoses in the future. The information provided by the expert system was also considered easy to comprehend, with effective language use. Features such as the history of previous diagnoses and disease diagnosis also received positive ratings from respondents, with the majority being satisfied with their use. Furthermore, respondents claimed they did not experience any errors while using the expert system. This indicates that the expert system has been well-designed and can be relied upon to provide service to users.

DISCUSSION

The integration of expert systems and chatbots into healthcare has shown significant potential in improving diagnostic efficiency, especially for the early detection of diseases. This study focused on the use of an expert system-based chatbot for the early diagnosis of eye diseases, an area where timely detection is critical to prevent severe health issues. The findings of this study underscore both the advantages of the technology and the areas that require further enhancement. This study explored the use of an expert system-based chatbot for early eye disease diagnosis. The system achieved an accuracy of 87% in providing initial diagnoses. While promising, this level of accuracy is not sufficient to confirm a diagnosis definitively.

Expert systems with chatbot are best used as tools for early eye disease detection, with further evaluation by healthcare professionals needed for accurate diagnosis and treatment. This aligns with previous research, such as (Sabaner et al., 2024), which showed similar diagnostic accuracy in rule-based systems for healthcare.

The user feedback was generally positive, with 84.75% of participants expressing satisfaction. The system's interface was considered easy to use, and the response time was adequate, echoing findings by (Sun et al., 2024), who highlighted the importance of user-friendly interfaces in healthcare chatbots. While the system provided quick responses and easy-to-understand information, some respondents felt the diagnostic accuracy could be improved. Overall, the feedback shows the expert system is a useful tool for initial eye disease diagnosis. However, improvements in diagnostic accuracy are needed, and integrating machine learning and image recognition could enhance its capabilities. This would help the system handle more complex conditions and increase user confidence in its results.

CONCLUSION

This research developed a chatbot-based expert system for the early diagnosis of eye diseases using the Naive Bayes method. The system integrates the expert knowledge of eye disease symptoms and their probabilities into a chatbot interface on the Telegram platform, providing a user-friendly and accessible diagnostic tool. The expert system demonstrated an 87% accuracy rate in initial diagnoses, as validated against specialist evaluations, proving its potential utility in facilitating early disease detection and management. Additionally, the system received a positive acceptance rate from users, as evidenced by the User Acceptance Test, where it achieved an average acceptance rate of 84.75%. This high level of user satisfaction underscores the effectiveness of the chatbot interface and the expert system's performance in providing prompt and reliable health diagnoses. The implementation of this system could greatly assist in the early detection and management of eye conditions, particularly in settings lacking sufficient medical infrastructure or specialist care. Thus, this research makes a significant contribution to expert system development, paving the way for easier and more efficient solutions in diagnosing eye diseases through an innovative platform. Suggestions for future research include improving the accuracy of the initial diagnoses generated by the system by incorporating other methods such as fuzzy logic combined with Naive Bayes. Another suggestion is to consider the use of Natural Language Processing (NLP) to make the system more interactive.

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