Journal of Information Systems and Informatics
Vol. 7, No. 1, March 2025 e-ISSN: **2656-4882** p-ISSN: **2656-5935**
DOI: 10.51519/journalisi.v7i1.950 Published By DRPM-UBD

Expert System for The Diagnosis of Depression in Students Using Certainty Factor Method: A Case Study of Ngudi Waluyo University

Yessy Sabilla Purnamasari[1], Sri Mujiyono[2], Fiktina Vifri Ismiriyam[3]

[1,2] Teknik Informatika, Univeristas Ngudi Waluyo, Indonesia
[3] Psikolog, Universitas Ngudi Waluyo, Indonesia
Email: [1]yessysabillaaa@gmail.com, [2]mujiyn80@gmail.com, [3]fiktinavifriismiriyam@yahoo.co.id

Abstract

Depression is a growing mental health concern among university students, often fueled by academic pressure, social demands, and personal stress. This study presents the development of an expert system using the Certainty Factor (CF) method to diagnose depression specifically among students at Ngudi Waluyo University. The system categorizes depression into mild, moderate, and severe levels based on 12 validated symptom statements and expert-defined diagnostic rules. Implemented with PHP, JavaScript, and CSS, the system offers a user-friendly, accessible, and anonymous platform for self-assessment. Testing yielded an accuracy rate of up to 79% in diagnosing depression severity and a 71.7% user satisfaction rate based on a User Acceptance Test (UAT) involving 32 students. Results demonstrate that the system can effectively support early detection and mental health awareness within academic environments. Despite some limitations in UI and feedback depth, the expert system shows strong potential for broader application and further enhancement.

Keywords: Depression Diagnosis, Expert System, Certainty Factor, Mental Health, University Students

1. INTRODUCTION

Depression is becoming an increasingly urgent mental health issue among university students, exacerbated by pressures related to academic demands, social expectations, and personal stressors. These challenges can significantly impair students' academic achievements, disrupt their social relationships, and diminish their overall quality of life when left unrecognized or untreated [1], [2]. A closer look at the 2023 mental health data from Semarang Regency reveals a worrying trend: as of October, 935 cases of mental health disorders were reported, including 445 cases of depression, 276 cases of mixed anxiety and depression, and 116 cases of insomnia [3]. These figures highlight an escalating public health concern that calls for immediate, structured, and long-term mental health interventions, not only through medical channels but also with support from community and governmental efforts [4], [5].

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Despite the growing prevalence of depression, a critical gap exists in how universities address student mental health. Many higher education institutions, particularly in developing regions, operate with minimal mental health infrastructure. Limited counseling services, long wait times, and underfunded psychological support are common. Mental health systems tend to be reactive, responding only when symptoms worsen rather than emphasizing early diagnosis and prevention. Geographic and economic barriers further complicate access, while social stigma often discourages students from seeking help. Consequently, many cases of depression remain undiagnosed or untreated, allowing the condition to escalate unchecked [6].

This study addresses these systemic shortcomings by designing an expert system based on the Certainty Factor (CF) method, specifically tailored for Ngudi Waluyo University students. The primary aim is to create a digital diagnostic tool that can assist both students and university counselors in identifying depressive symptoms accurately and efficiently. Unlike traditional methods, this system offers fast, anonymous, and round-the-clock access, enabling students to assess their mental health without the fear of judgment or the logistical burden of face-to-face appointments. Such accessibility not only improves diagnosis rates but also empowers students to take proactive steps toward managing their mental well-being.

Previous studies in depression diagnostics often overlook the unique psychosocial landscape of university students, treating depression in a generalized context without accounting for distinct stressors such as academic overload, financial pressure, and the emotional challenges of transitioning into adulthood [7], [8]. Furthermore, while the CF method has been effectively used in medical expert systems, its application in a student-specific setting—and its integration with real-time data from mobile applications or wearable devices—remains underexplored. With past implementations of CF-based expert systems achieving diagnostic accuracy rates of up to 97%, its potential in this context is significant [9], [10], [11]. This research not only implements the CF method for this demographic but also considers future enhancements such as technology integration and multidisciplinary collaboration to strengthen diagnostic precision.

Additionally, current diagnostic systems rarely offer follow-up actions beyond symptom identification. This study aims to remedy that by incorporating post-diagnosis features such as referrals to on-campus counselors, stress management strategies, and lifestyle recommendations tailored to the severity of the diagnosis. The scalability of such a system means it can assist thousands of students simultaneously, alleviating pressure on university mental health services while ensuring no student is left behind. Ultimately, this expert system aspires to normalize mental health conversations, enhance institutional support structures,

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

and improve academic and social outcomes for students [12]. With its accessible design and evidence-based methodology, the system offers a promising solution to an urgent and growing challenge within higher education.

2. METHODS

This research utilized a quantitative approach integrated with expert system development and user testing to assess the feasibility and accuracy of a depression diagnosis tool tailored for university students. A User Acceptance Test (UAT) served as the primary evaluation framework, involving both end-users (students) and domain experts (psychologists and counselors). The UAT was conducted through structured questionnaires designed to capture feedback on the system's functionality, user interface, and diagnostic accuracy. Simultaneously, qualitative data was gathered through interviews and observations, enabling researchers to understand how users perceived and interacted with the system. These data sources complemented one another, ensuring a rich, multi-dimensional understanding of how well the system could operate in a real academic environment and fulfill its objective of early detection and mental health support.

To construct the system, the System Development Life Cycle (SDLC) using the Waterfall model was adopted due to its structured, linear process that ensures thorough planning and implementation. This model comprises six core stages. The first, Requirement Analysis, involved gathering essential data related to depression symptoms, severity indicators, and diagnostic rules. This data was obtained through consultations with professional psychologists and university counselors, ensuring the knowledge base was grounded in clinical expertise. During the System Design phase, the architecture of the expert system was outlined, including user interface mockups, flowcharts, and the logical framework for the Certainty Factor method. In the Implementation stage, the expert system was coded using PHP, JavaScript, and CSS, incorporating a robust interface and a backend capable of processing and calculating CF values based on user input.

The next phase, System Testing, involved rigorous validation using simulated case scenarios that represented mild to severe depression. These test cases helped identify logical flaws, technical bugs, or usability issues. Errors were addressed promptly before deployment. Once the system was deemed functional, it entered the Maintenance phase, during which feedback from users and experts was incorporated to fine-tune both content and design. The final Evaluation stage assessed the effectiveness, accuracy, and impact of the system in diagnosing depression among students. By leveraging these structured phases, the system was built systematically and refined iteratively to meet academic, psychological, and technical standards [13].

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Primary and secondary data were critical in shaping the expert system's knowledge base. Primary data was sourced directly from expert interviews with mental health professionals, particularly psychologists, who provided firsthand insights into depression symptoms, levels of severity, and appropriate interventions [15]. These interviews were semi-structured to allow in-depth discussions while maintaining comparability across responses. Secondary data, meanwhile, was collected through a literature review of existing studies on depression diagnosis, Certainty Factor applications, and expert system design. This dual-sourcing strategy ensured the knowledge base was both theoretically grounded and contextually relevant. Additionally, student survey data was collected, cleaned, and preprocessed to remove inconsistencies and ensure data quality before integration into the system.

The Certainty Factor (CF) method served as the core diagnostic engine for the expert system. This rule-based reasoning model is particularly effective in managing uncertainty, a frequent challenge in psychological assessments. In CF, every symptom or indicator is assigned a Measure of Belief (MB) and a Measure of Disbelief (MD). The basic formula is shown in Equation 1.

$$CF = MB - MD \tag{1}$$

This determines the strength of evidence supporting a diagnosis. For multiple symptoms, CF values are combined recursively using the formula as shown in Equation 2.

$$CFcombined = CF1 + CF2 \times (1 - CF1) \tag{2}$$

For instance, if a student reports "persistent sadness" (CF = 0.7) and "loss of interest" (CF = 0.8), the combined CF is as shown in Equation 3.

$$CFcombined = 0.7 + 0.8 \times (1 - 0.7) = 0.94 \tag{3}$$

This result indicates a 94% confidence level in diagnosing depression. The CF approach thus provides flexibility in incorporating varying symptom weights and allows the system to generate nuanced diagnostic outputs. Previous research in medical informatics has shown CF to be effective in domains such as diabetes diagnosis, cardiovascular risk prediction, and mental health assessment [13], [14].

Following deployment, the system was integrated into a university platform to allow live access for students. A six-month pilot implementation was conducted to assess its real-world applicability. During this period, usage logs, feedback, and diagnostic outcomes were collected and analysed. Statistical tools such as confusion matrices, precision-recall metrics, and correlation analyses were used to evaluate the system's diagnostic accuracy against expert-verified cases. The

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

expert system also featured a dynamic questionnaire, adapted from DSM-5 criteria, covering symptoms such as fatigue, low mood, and concentration issues. Responses were scored using a 5-point Likert scale, and the data was used to feed the CF engine and generate a diagnosis. Demographic data—including age, academic year, and field of study—was also collected to identify risk patterns and tailor future interventions.

In the final stage, system testing and analysis validated the model's real-time accuracy in diagnosing depression and providing actionable outcomes. Users were guided through symptom selection, and the system calculated the depression severity using CF logic. Depending on the output, personalized suggestions were generated, ranging from general wellness tips to direct referrals to campus counseling services. This expert system not only improved efficiency in early diagnosis but also offered an accessible, scalable, and stigma-free mental health resource for Ngudi Waluyo University students [15]. The implementation highlights the potential of integrating intelligent systems into educational settings to bridge the existing mental health service gap.

3. RESULTS AND DISCUSSION

3.1. Data Analysis and Symptom Classification

The initial phase of this study focused on gathering clinical insights through expert consultation. Mental health professionals played a vital role in providing detailed information on depression symptoms, severity levels, and diagnostic indicators [16], [17]. This expert input was critical in designing a system that reflects real-world diagnostic logic, ensuring it captures the nuances of depressive disorders as experienced by university students. Based on this consultation, depression was classified into three primary categories: mild, moderate, and severe depression. These levels serve as the foundation for personalized responses and targeted recommendations within the expert system. Table 1 presents the structured classification used in the system.

Each category corresponds to a particular combination of symptoms, enabling the system to evaluate a user's input and accurately determine their mental health status. For example, mild depression may manifest through low energy or sadness, while severe depression often involves more serious symptoms like cognitive dysfunction or hallucinations. This structure ensures that the system not only identifies depression but also pinpoints its severity, which is essential for recommending suitable intervention strategies.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Table 1. Levels of Depression

No	Depression Codes	Name of Depression
1.	D1	Mild Depression
2.	D2	Moderate Depression
3.	D3	Severe Depression

Following the depression level classification, the research team compiled a comprehensive list of 12 symptom statements. These were developed based on clinical observations and patterns commonly reported during student counseling sessions. The goal was to capture a wide range of emotional, physical, and behavioral symptoms that align with established diagnostic criteria. Table 2 provides the complete list of symptom statements and their corresponding codes.

Table 2. Symptoms Statement Data

Code	Statement
A001	I am suddenly sad when there is no apparent cause for sadness.
A002	I become fatigued with minimal exertion, despite the absence of strenuous activity.
A003	I frequently perceive myself as worthless and ascribe blame to myself for circumstances beyond my control.
A004	I lack motivation when attempting to complete tasks.
A005	I often experience shortness of breath due to the pressure I face.
A006	I have trouble sleeping, which often results in staying up late.
A007	I have lost weight due to a lack of appetite.
A008	My reflexes have slowed down in some joints of my body.
A009	I am less able to care for myself.
A010	I have difficulty concentrating when attempting to complete tasks. I have difficulty managing my time.
A011	I experience hallucinations that interfere with my daily life.
A012	I am suddenly sad when there is no apparent cause for sadness.

Each symptom was then grouped into diagnostic rules, which form the decision-making logic within the expert system. The rules are as follows:

1) Rule 1: Mild Depression
   If the user reports A001, A002, A003, and A004, the system classifies it as Mild Depression.
2) Rule 2: Moderate Depression
   If the user reports A005, A006, A007, and A008, the system classifies it as Moderate Depression.
3) Rule 3: Severe Depression
   If the user reports A009, A010, A011, and A012, the system classifies it as Severe Depression.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

These rules help simplify complex symptom data into actionable outputs, allowing for fast, accurate, and explainable decisions.

3.2. Certainty Factor Calculation and Diagnostic

To manage diagnostic uncertainty and varying symptom intensities, the system employs the Certainty Factor (CF) method. Each symptom is assigned a confidence value between 0.1 and 1.0, reflecting how strongly it contributes to a particular depression type. These values were assigned based on expert opinions and previous studies [18].

Table 3. presents the CF values assigned to each symptom

Code	Symptom Description	CF Value
A001	Sudden sadness	0.3
A002	Fatigue without exertion	0.3
A003	Feelings of worthlessness	0.2
A004	Lack of motivation	0.4
A005	Shortness of breath	0.5
A006	Trouble sleeping	0.5
A007	Loss of appetite	0.6
A008	Slowed reflexes	0.4
A009	Inability to care for self	0.7
A010	Difficulty concentrating	0.8
A011	Difficulty managing time	0.8
A012	Hallucinations	0.6

These values are combined using the following formula as shown in Equation 4.

$$CFcombined = CF1 + CF2 \times (1 - CF1) \tag{4}$$

This recursive formula accounts for multiple symptoms contributing to a diagnosis. The final CF values calculated for each depression type in a sample test case are:

1) Mild Depression
   CF(A001 & A002) = 0.3 + 0.3 × (1 – 0.3) = 0.51
   Add A003: 0.51 + 0.2 × (1 – 0.51) = 0.608
   Add A004: 0.608 + 0.4 × (1 – 0.608) = 0.764
2) Moderate Depression
   CF(A005 & A006) = 0.5 + 0.5 × (1 – 0.5) = 0.75
   Add A007: 0.75 + 0.6 × (1 – 0.75) = 0.9
   Add A008: 0.9 + 0.4 × (1 – 0.9) = 0.94
3) Severe Depression
   CF(A009 & A010) = 0.7 + 0.8 × (1 – 0.7) = 0.94

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

Add A011: $0.94 + 0.8 \times (1 - 0.94) = 0.988$
Add A012: $0.988 + 0.6 \times (1 - 0.988) = 0.995$

The results indicate that severe depression had the highest CF score (99.5%) in this particular case, suggesting an urgent mental health issue. This demonstrates the effectiveness of the CF method in ranking depression severity and guiding appropriate intervention. With an accuracy rate of up to 79%, the system compares favourably to traditional methods and even some machine learning approaches, especially given its simplicity and explainability.

3.3. Interface Design and System Functionality

To ensure accessibility and ease of use, the expert system was built using PHP for backend logic, JavaScript for interactivity, and CSS for styling and responsive design [19], [20], [21]. The interface was carefully designed to guide users step-by-step through the mental health self-assessment process in a friendly and non-threatening manner. The first touchpoint for users is the Main Page, as shown in Figure 1. This homepage serves as both a welcoming gateway and an informational hub. It offers a brief yet comprehensive overview of what depression is, what causes it, and why early detection is critical. The design uses calm colors and accessible language to ease users into what can often be a sensitive topic. The intention here is clear: before diving into any diagnosis, users are given the knowledge and assurance they need to proceed with confidence. After familiarizing themselves with the topic, users proceed to the Diagnosis Menu, displayed in Figure 2.

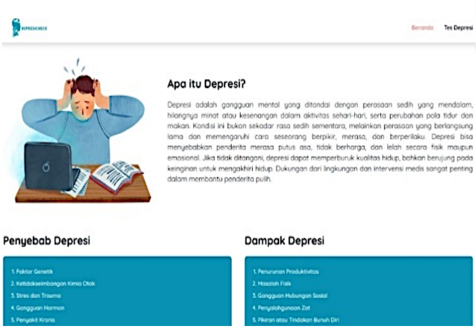

Figure 1. Main Page

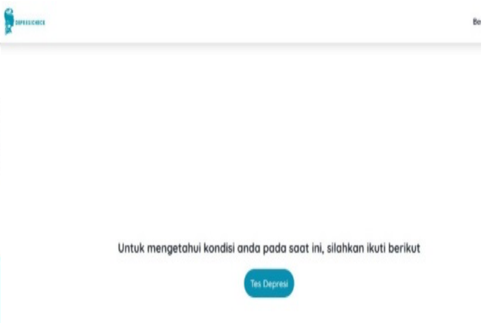

Figure 2. Diagnosis Menu

This menu is clean and simple, presenting the user with a clear path: begin the depression self-test. This interface was intentionally designed to reduce decision fatigue and confusion. Students, who are often overwhelmed by academic and social pressures, benefit from this intuitive layout that directs them quickly and clearly to the next action. Once the user enters the diagnostic process, the system

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

presents 12 carefully structured questions, each corresponding to specific depression symptoms identified during earlier expert consultations. As depicted in Figure 3, the user is prompted with questions like, "Do you often feel sad without any apparent reason?" These questions use informal, relatable language that resonates with students' daily emotional experiences. Each response is internally linked to a CF value, allowing the system to continuously calculate the probability of depression severity as the questionnaire progresses. Finally, once all questions are answered, the user is shown the results screen. Figure 4 display offers more than just a percentage—it interprets the user's responses and provides a probable depression category (mild, moderate, or severe). In addition, users are presented with actionable suggestions tailored to their result. This could include encouraging mindfulness practices, seeking counseling support, or simply tracking their mood over the coming weeks. The inclusion of practical advice transforms the system from a passive diagnostic tool into an active mental wellness assistant.

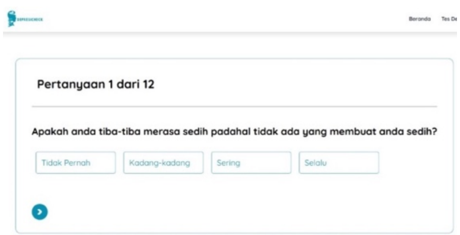

Figure 3. Diagnosis Process

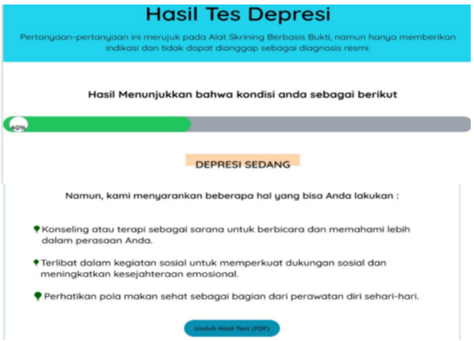

Figure 4. Depression Test

3.4. User Acceptance Test (UAT)

To evaluate the effectiveness, usability, and user satisfaction of the developed expert system, a User Acceptance Test (UAT) was conducted with 32 students from Ngudi Waluyo University. These participants were selected randomly across various academic years and study programs to ensure diversity in perspectives and experiences. After interacting with the system, each participant completed a feedback questionnaire designed to assess key performance indicators such as usability, clarity, functionality, and overall satisfaction. The questionnaire employed a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), enabling precise measurement of user sentiments. The total score accumulated from all participants was 1,147 points. When this score was averaged across the 32 users, it yielded an individual average score of 35.85 out of a maximum of 50. To better understand the acceptance rate in percentage terms, this value was converted using the formula as shown in Equation 5.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

$$\text{Percentage Score} = (35.85 / 50) \times 100\% = 71.7\% \quad (5)$$

This 71.7% satisfaction rate reflects a moderately high level of acceptance for the system's usability and perceived usefulness. The results indicate that the system effectively meets the basic expectations of users in helping them understand and assess their mental health status. However, the feedback also pointed toward several key areas that require further development, highlighting the iterative nature of user-cantered design, especially in sensitive fields like mental health.

3.5. Usability Implications and Future Development

The UAT provided not only quantitative data but also qualitative insights that reveal the strengths and shortcomings of the current system version. Students expressed appreciation for several core features, while also identifying opportunities to enhance the user experience. One of the most notable strengths was the clarity and logic behind the diagnostic process. Users felt that the system's structured flow from symptom-based questions to diagnosis and recommendation was both intuitive and informative. It allowed them to understand the logic behind their results, thereby fostering trust in the system's credibility. Moreover, the system's digital and anonymous nature was highlighted as a major benefit. Many students shared that they felt more comfortable engaging with the system than seeking help from a counsellor face-to-face, a reflection of the social stigma that often surrounds mental health issues.

Despite these strengths, several areas for improvement were noted. The most common suggestion was to enhance the user interface (UI). Although the system was functional, some users found the layout too basic. They recommended incorporating visual elements like progress bars, calming colour schemes, and animations to make the experience more engaging and emotionally supportive. Another concern was the depth of feedback provided post-diagnosis. While users appreciated knowing their depression level, they wanted more detailed guidance, such as coping strategies, lifestyle tips, or direct links to on-campus mental health services. Additionally, a few users commented on the emotional tone of the final screen, suggesting that more empathetic, encouraging language would make the results feel less clinical and more comforting.

To increase engagement and long-term usage, students proposed several enhancement strategies. First, the system could integrate educational content, such as short videos, mental health articles, or mindfulness practices, to help users better understand their condition. Second, adding gamification elements like earning badges for completing check-ins or reaching mental wellness milestones could make the system more interactive. Third, mobile optimization or the development of a dedicated smartphone app was seen as crucial, especially

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

considering students' reliance on mobile devices. Lastly, students strongly supported the idea of real-time integration with campus services, including options to book appointments with a counsellor or initiate a live chat directly through the platform.

From a broader institutional perspective, the system demonstrates strong potential for scaling mental health support across the university. By providing consistent and accessible mental health screening, it can help identify at-risk students early and connect them to appropriate support services. This proactive approach not only improves student well-being but may also positively impact academic performance, retention, and campus safety. The initial 71.7% satisfaction score, while leaving room for growth, establishes a solid foundation for iterative development. With continued refinement and institutional backing, the expert system can evolve into a vital tool for promoting mental wellness in academic environments.

3.6. Discussion

The development and evaluation of the expert system for depression diagnosis using the Certainty Factor (CF) method have yielded significant insights into the feasibility and effectiveness of deploying intelligent systems for mental health support in university environments. The findings from the data analysis, CF calculations, and User Acceptance Test (UAT) reveal both the promise and the challenges inherent in building such systems.

First and foremost, the use of the CF method proved to be a practical and explainable way to handle uncertainty in symptom-based diagnosis. By quantifying the confidence levels for each symptom and combining them systematically, the system was able to categorize depression severity with a maximum confidence level of 99.5% and an overall diagnostic accuracy reaching 79%. These results affirm the CF method's capacity for accurate early screening, especially in contexts where full clinical assessments may not be readily available. Moreover, the system's design, grounded in rules validated by expert psychologists, ensures that the diagnostic outputs are not arbitrary but reflective of established clinical practices.

The user experience results further validate the system's effectiveness. The UAT score of 71.7% indicates a generally positive reception among students, especially with regard to ease of use, accessibility, and diagnostic clarity. This level of acceptance is particularly meaningful considering the topic's sensitivity and the tendency for mental health issues to be underreported due to social stigma or lack of awareness. The expert system offers a private, stigma-free space for students to reflect on their mental health and obtain initial assessments—an

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

advantage that cannot be understated in university settings where resources are often stretched thin.

However, the findings also bring attention to several areas that warrant improvement. One of the key concerns raised by users was the need for more emotionally supportive and engaging feedback. While the system's logic was respected, the tone of the output and the interface design were considered too formal or minimal by some users. This highlights the importance of human-cantered design, particularly when addressing mental health, where empathy and emotional reassurance are essential components of effective support.

Another limitation involves the static nature of the knowledge base and diagnosis process. While the CF method allows for efficient symptom processing, it lacks the adaptability of more dynamic models like machine learning, which can improve continuously through large-scale data input. The current system, while robust, does not yet utilize real-time data from wearable technology, mood trackers, or other digital sources that could significantly enhance the accuracy and personalization of depression diagnosis.

Moreover, the study's scope is limited to a single university, which affects the generalizability of the results. Student experiences with mental health can vary significantly across regions, cultures, and academic pressures. Therefore, to fully validate the system's effectiveness, future iterations should include broader testing across multiple institutions and demographic groups. Expanding the sample size and including diverse backgrounds would help in refining the symptom library and response patterns to ensure relevance across various student populations.

Despite these limitations, the expert system serves as an important first step toward digital mental health integration in academic institutions. Its benefits—such as 24/7 accessibility, anonymity, rapid screening, and the potential for high scalability position it as a valuable tool for preventive mental health care. Universities, especially those with limited access to professional counsellors, can benefit immensely by adopting or adapting such technology to extend their mental health services beyond traditional boundaries.

Finally, while this CF-based expert system is not intended to replace professional diagnosis, it is highly effective as a complementary tool for early detection, awareness-raising, and user guidance. The system bridges the gap between silence and support, making mental health care more approachable, especially for students who may otherwise suffer in silence. With ongoing refinement, stakeholder engagement, and institutional backing, the system has the potential to become a cornerstone of student mental wellness programs in the digital era.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

4. CONCLUSION

This study successfully developed an expert system for diagnosing depression among university students using the Certainty Factor (CF) method. The system effectively identifies depression levels—mild, moderate, and severe—based on user-inputted symptoms and provides initial guidance for follow-up actions. With an accuracy rate of up to 79% and a user satisfaction level of 71.7%, the system shows strong potential as a supportive mental health tool. Its accessibility, anonymity, and ease of use make it especially valuable in educational settings where mental health resources may be limited. While improvements are needed in interface design and post-diagnosis feedback, the system offers a scalable, practical solution for early detection and increased mental health awareness on campus. Continued development and integration into university support services could significantly enhance student well-being.

REFERENCES

[1] A. H. Ibrahim, "Depression, anxiety and stress among first year medical students in Malaysia," *J. Ment. Health*, vol. 22, no. 1, pp. 33–37, 2013, doi: 10.3109/09638237.2012.656964
[2] R. A. Dani and D. A. Wicaksono, "Kemampuan activity of daily living pada anak gangguan spektrum autis ditinjau dari pengetahuan orang tua tentang autisme dan penerimaan diri orang tua," in *Pros. Sem. Nas. Psikol. UNNES*, vol. 4, 2023.
[3] A. Imron, "Transformasi UU Kesehatan: Peran Tenaga Kesehatan dalam Sistem Ketahanan Nasional Indonesia," in *Pros. Sem. Nas. Kesehatan*, 2023.
[4] E. Widodo and S. Jaya, "Implementsi Sistem Pakar Untuk Mendiagnosa Tingkat Depresi Pada Mahasiswa Tingkat Akhir Dengan Metode Certainty Factor," *J. Tek. Pelita Bangsa-SIGMA*, vol. 8, no. 2, pp. 233–240, 2018.
[5] F. Y. R. M. Marpaung, Z. Azmi and D. Suherdi, "Sistem Pakar Mendeteksi Tingkat Depresi Dengan Menggunakan Metode Certainty Factor," *J. Sist. Inf. TGD*, vol. 1, no. 6, pp. 732–740, 2022.
[6] G. V. G. Putri, "Sistem Pakar Diagnosa Mental Ilness Psikosis dengan Menggunakan Metode Certainty Factor," *J. Inovtek Polbeng - Seri Inform.*, vol. 3, no. 2, pp. 164–168, 2018.
[7] M. F. U. A. Siddieq, "Sistem Pakar Diagnosa Depresi Mahasiswa Tingkat Akhir dengan Metode Certainty Factor dan Forward Chaining," *J. Sains dan Teknol.*, vol. 3, no. 7, pp. 1–10, 2024.
[8] M. F. U. A. Siddieq, "Sistem Pakar Diagnosa Depresi Mahasiswa Tingkat Akhir dengan Metode Certainty Factor Dan Forward Chaining," *J. Multidisiplin Saintek*, vol. 3, no. 7, pp. 1–10, 2024.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[9] E. W. Sholeha, B. Sabella, W. Kusrini and S. Komalasari, "Sistem Pakar Penyakit Mental Remaja Menggunakan Metode Forward Chaining dan Certainty Factor," *Kumpul. J. Ilmu Komput.*, vol. 10, no. 1, pp. 82–91, 2023.

[10] E. Widodo and S. Jaya, "Implementsi Sistem Pakar Untuk Mendiagnosa Tingkat Depresi Pada Mahasiswa Tingkat Akhir dengan Metode Certainty Factor," *J. Tek. Pelita Bangsa*, vol. 8, no. 2, pp. 233–240, 2018.

[11] R. Aprilyani, "Bab 6 Assessment dalam Psikologi Klinis: Interview dan Behavioral," in *Psikol. Klinis*, vol. 69, 2022.

[12] H. Mayatopani, R. Subekti, N. Yudaningsih, and M. Sanwasih, "Pengembangan sistem pakar diagnosa gangguan mental dengan mesin inferensi menggunakan algoritma Dempster-Shafer Theory," *J. Buana Inform.*, vol. 13, no. 1, pp. 66–76, 2022.

[13] S. Nickels et al., "Toward a mobile platform for real-world digital measurement of depression: user-centered design, data quality, and behavioral and clinical modeling," *JMIR Ment. Health*, vol. 8, no. 8, p. e27589, Aug. 2021.

[14] R. A. Nurimansjah, "Application of Web-Based Certainty Factor Method to Develop an Employee Job Stress Diagnosis System to Improve Employee Performance," *J. Inf. dan Teknol.*, vol. 10, no. 2, pp. 252–257, 2023.

[15] I. Efendi, R. K. Niswatin, and I. N. Farida, "Penerapan Metode Certainty Factor untuk Sistem Pakar Diagnosa Penyakit Burung Puyuh Berbasis Web," in *Semin. Nas. Inov. Teknol.*, 2020.

[16] R. Retnowati and A. Pujiyanta, *Implementasi Case Base Reasoning pada Sistem Pakar dalam Menentukan Jenis Gangguan Kejiwaan*, Disertasi Doktor, Universitas Ahmad Dahlan, 2013.

[17] N. A. Raharisti, V. Atina, and D. Hartanti, "Penerapan metode Dempster-Shafer pada sistem pakar diagnosis penyakit kejiwaan," *Infotek: J. Inf. dan Teknol.*, vol. 7, no. 2, pp. 467–477, 2024.

[18] N. N. Santoso, Y. Maulita, and H. Khair, "Sistem Pakar Diagnosa Tingkat Depresi Mahasiswa Tingkat Akhir Dengan Menggunakan Metode Certainty Factor," *BIMASATI (Bull. Multidisiplin Sci. Appl. Technol.)*, vol. 1, no. 5, pp. 153–158, 2022.

[19] R. T. Aldisa, "Sistem Pakar Mendeteksi Kondisi Kesehatan Mental Dengan Metode Forward Chaining Berbasis Android," *J. Riset Komput.*, vol. 9, no. 2, pp. 396–403, 2022.

[20] H. Hasanah, R. Ridarmin, and S. Adrianto, "Aplikasi sistem pakar pendeteksi kerusakan laptop/PC dengan penerapan metode Forward Chaining menggunakan bahasa pemrograman PHP," *Informatika*, vol. 9, no. 2, pp. 40–50, 2019.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[21] H. Hasanah, R. Ridarmin, and S. Adrianto, "Aplikasi sistem pakar pendeteksi kerusakan laptop/PC dengan penerapan metode Forward Chaining menggunakan bahasa pemrograman PHP," *J. Informatika*, vol. 9, no. 2, pp. 40–50, 2019.