Detecting Post-Traumatic Stress Disorder Trauma with Hybrid Expert System and Machine Learning

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Abstract

Post-Traumatic Stress Disorder (PTSD) remains a critical mental health challenge, yet conventional diagnostics often struggle with subjective bias and linguistic ambiguity. This research addresses these limitations by developing a Hybrid Expert System that integrates Forward Chaining with a Random Forest machine learning algorithm to classify PTSD trauma severity into three levels: Low, Medium, and High. The hybrid architecture combines rigid clinical logic with adaptive pattern recognition to better interpret complex patient narratives. To overcome the prevalent issue of class imbalance in medical data, the Synthetic Minority Over-sampling Technique (SMOTE) was employed. Experimental results demonstrate that the proposed system achieves a high accuracy of 99.02%, significantly outperforming traditional keyword-matching methods and standalone rule-based systems. While maintaining high precision, the integration of SMOTE successfully enhanced the model's sensitivity in detecting severe trauma cases. This study underscores the importance of hybrid intelligence in mental health informatics, providing a more objective, transparent, and reliable diagnostic tool. Such technology is vital for early clinical intervention, potentially reducing the long-term socio-economic impact of undiagnosed psychological trauma and supporting medical professionals in delivering more accurate mental health services.

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Keywords*—Forward Chaining, Hybrid Expert System, PTSD, Random Forest, SMOTE*

1. INTRODUCTION

Post-Traumatic Stress Disorder (PTSD) represents one of the most pressing mental health challenges in the modern era. Reports from the World Health Organization (WHO) indicate that while the global prevalence of PTSD reaches 3.9%, it surges to 15.3% among populations exposed to armed conflict and sexual violence. Demographically, the risk of this disorder is recorded to be higher in women than in men, primarily due to the chronic psychological impact of the traumatic events experienced [1]. In Indonesia, data from the Ministry of Health shows that cases of post-traumatic stress disorder are increasing, particularly among victims of natural disasters and domestic violence, resulting in a significant social and economic burden [2]. Clinically, sufferers often experience persistent symptoms such as flashbacks, pathological anxiety, and sleep disturbances, which have a broad impact on declining productivity in the social and economic sectors. This condition aligns with the latest Global Burden of Disease reports, which confirm that PTSD is a major contributor to persistent functional impairment, where the disability levels of those affected are found to be more severe than various chronic physical conditions [3]. Without proper early detection, undiagnosed trauma risks developing into chronic disorders that are far more complex to treat. Therefore, a rapid and accurate trauma-level identification system is required to support medical professionals in providing targeted interventions.

However, in practice, conventional diagnosis still faces significant accuracy limitations. It often relies on subjective assessments prone to bias, while sufferers frequently struggle to express their condition consistently. Efforts to digitalize trauma detection have begun to emerge through various computational approaches. The diagnostic process typically depends on clinical interviews and medical professionals' subjective evaluations, which are susceptible to interpretative bias. Furthermore, PTSD sufferers often find it difficult to articulate their experiences consistently thus, the information obtained

does not always reflect the true severity of the trauma. Recent literature highlights that traditional manual questionnaire-based methods are less capable of capturing the complexity of a patient's emotional narrative, especially when the language used is ambiguous or indirect [4]. This leads to a high risk of both underdiagnosis (undetected severe trauma) and overdiagnosis (excessive diagnosis due to misinterpretation). Along with technological advancements, the trend of using Artificial Intelligence (AI) in mental health is on the rise. Various studies demonstrate that the integration of AI, specifically Natural Language Processing (NLP) and Machine Learning, can help analyze linguistic patterns and emotions in patient narratives more objectively and consistently [5].

In addition, the concept of Explainable AI (XAI) is also beginning to be applied to ensure that system decisions remain transparent and understandable for medical professionals. Previous research [4], has shown that the Forward Chaining method is quite effective in performing the initial classification of anxiety disorders based on structured clinical symptoms. However, previous studies [6], which focused on detecting Domestic Violence (DV) using the Keyword Matching method, still have limitations in handling linguistic ambiguity. These systems are only capable of identifying indicators of violence in a binary fashion (yes/no), without providing an overview of the trauma's severity levels. This weakness is also found in other mental health research, where pure expert systems lack flexibility when facing the uncertainty of narrative data. The challenge of handling narrative data uncertainty has led other mental health studies to propose hybrid approaches to enhance the flexibility of pattern analysis [7].

In contrast to previous systems, this study aims to measure the trauma levels (PTSD) resulting from such violence in a more profound manner. By integrating a Hybrid Expert System, this system does not rely solely on keyword matching but also utilizes validated clinical datasets to determine the severity of trauma (mild, moderate, or severe). The hybrid approach, combining Forward Chaining and Machine Learning, is designed to bridge the rigidity of logical rules with the flexibility of pattern analysis, thereby addressing weaknesses in handling data uncertainty through the learning of more complex and dynamic narrative patterns. Consequently, this research contributes to the development of a trauma detection system that is more holistic, transparent, and adaptive to the natural language variations of PTSD sufferers, while simultaneously providing added value within the context of technology-based mental health services

2. RESEARCH METHODS

The methodology of this research is designed to develop a hybrid expert system capable of classifying the severity levels of trauma in PTSD sufferers. The hybrid approach was selected for its ability to combine the clarity of expert logic with the flexibility of machine learning algorithms in analyzing unstructured narrative data. Consequently, the system not only generates explainable decisions but is also capable of adapting to complex variations in natural language [8].

The research stages begin with Knowledge Acquisition, which involves constructing a rule-base derived from validated PTSD clinical instruments. The inference process is carried out using the Forward Chaining method, which traces symptom facts from user input toward an initial diagnostic conclusion [5]. To handle textual data, the system employs simple Natural Language Processing (NLP) techniques during the preprocessing stage to clean the textual data from user narratives before classification by the Random Forest model. This step is crucial to ensure that feature extraction from the victims' narratives is free from noise, thereby making the weighting of trauma severity levels (Mild, Moderate, or Severe) more accurate [6], [9].

Systematically, this hybrid architecture operates within a two-layer architecture. The first layer utilizes Forward Chaining logic to validate diagnostic criteria according to clinical standards. The second layer leverages a Random Forest model to analyze emotional intensity and patterns from the data that has undergone the NLP stage. The combination of these two layers produces a more precise and dynamic trauma level assessment compared to single rule-based systems [10].

2.1 Research Framework

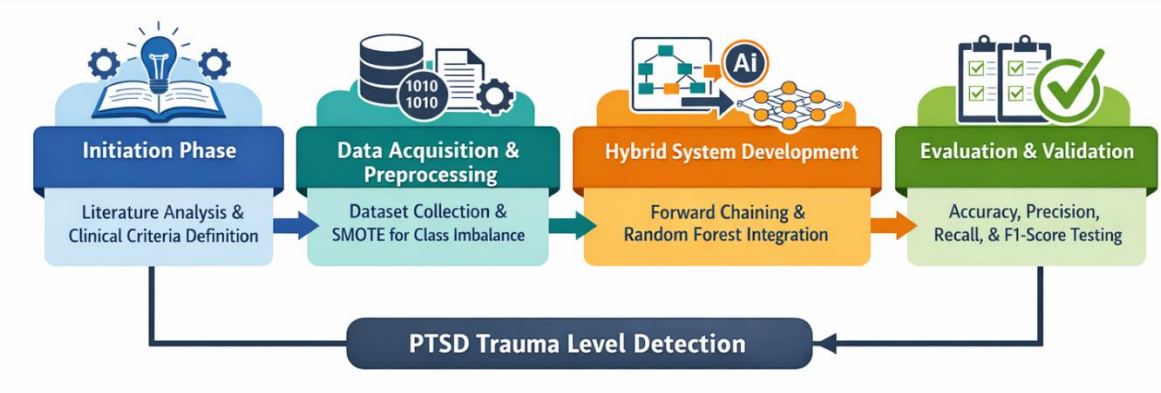


Figure 1. Research Framework for PTSD Trauma Level Detection

This research begins with an in-depth literature study regarding PTSD clinical criteria based on validated instruments, followed by the acquisition of datasets from public repositories. This stage aims to ensure that the system is built upon a solid theoretical foundation and robust empirical data. The next stage involves designing the rule-base for the Forward Chaining inference engine. These rules are structured to translate expert diagnostic logic into the computer system, ensuring that classification results possess clear traceability [11].

In parallel, the Random Forest model training is conducted. This algorithm was selected for its ability to handle non-linear features and provide high predictive stability on complex healthcare data [12]. Given that PTSD datasets often suffer from class imbalance, this research applies the SMOTE (Synthetic Minority Over-sampling Technique) technique. SMOTE is utilized to synthesize new data for the minority class, ensuring the model remains unbiased toward the majority class and improving detection sensitivity [11].

The final stage is the integration of both methods into a hybrid system. Within this architecture, Forward Chaining functions as a clinical logic filter, while Random Forest plays a role in providing predictive weighting based on narrative patterns. Performance evaluation is conducted using Accuracy, Precision, Recall, and F1-Score metrics to ensure system reliability before implementation [12]. The use of these various metrics aims to validate the system's ability to minimize diagnostic errors, both false positives and false negatives, which is highly crucial within the context of mental health [13].

2.2 Data Acquisition and Preprocessing

The supporting data for this research was obtained from the Mendeley Data repository titled "Comprehensive Post-Traumatic Stress Disorder (PTSD) Analysis Dataset for Demographic and Symptom Insights" [14]. This dataset contains recordings of various clinical features representing PTSD symptom indicators, which include narrative data and psychometric variables. Given that the characteristics of medical data are often concentrated in specific categories, this dataset exhibits an imbalanced class distribution. This condition may cause the model to lean toward a bias against the majority class, posing a risk of generating false negatives in the detection of severe trauma [15].

To address these challenges, this research implements the SMOTE (Synthetic Minority Over-sampling Technique) technique. Unlike conventional oversampling, which merely duplicates data, SMOTE works by creating synthetic samples within the feature space of the minority class using the k-nearest neighbors algorithm [16]. This implementation ensures that the model possesses a fair and balanced assessment weight across the Low, Medium, and High trauma level categories.

In addition to data balancing, the preprocessing stage involves data normalization and text cleaning. This process is crucial for removing noise from user narrative data, such as stopwords and punctuation, so that the linguistic feature extraction by the Machine Learning model becomes more optimal and accurate [17].

2.3 System Design (UML)

To illustrate the actor interactions and functional data flow within this hybrid system, Unified Modeling Language (UML) modeling is utilized through Use Case Diagrams and Activity Diagrams.

1. Use Case Diagram

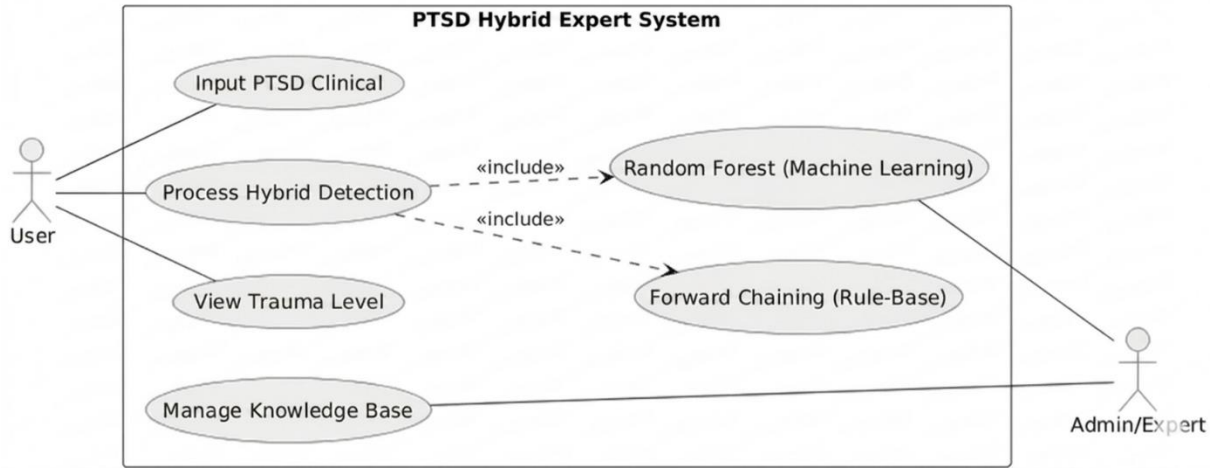


Figure 2. UML Use Case Diagram of PTSD Hybrid Expert System

Based on Figure 2, the Use Case Diagram divides the system authority into two primary actors: User and Admin/Expert.

a. **User:** Holds the functional role to perform Input PTSD Clinical, trigger Process Hybrid Detection, and View Trauma Level.
b. **Admin/Expert:** Responsible for managing the Knowledge Base to ensure that clinical rules remain up-to-date.
c. **Relasi *Include*:** The hybrid detection process automatically encompasses (includes) two core sub-processes: Forward Chaining-based analysis (Rule-Base) and prediction via Random Forest (Machine Learning). This indicates that the final decision is the result of the simultaneous integration of both methods.

2. Activity Diagram

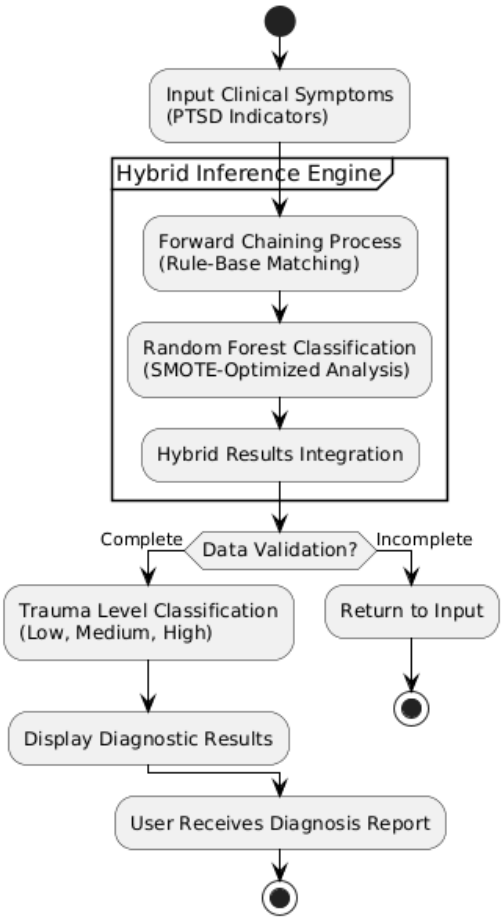


Figure 3. Flowchart of PTSD Hybrid Diagnostic Process

The Flowchart Diagram in Figure 3 details the sequential and integrated data workflow within the system:

a. **Input Stage:** The system receives clinical symptom data (Input Clinical Symptoms) from the user.
b. **Hybrid Inference Engine:** This represents the core of the system, where data is processed sequentially through the Forward Chaining Process for rule matching, followed by optimization with Random Forest Classification which has undergone SMOTE-Optimized Analysis. The outputs from both approaches are then consolidated in the Hybrid Results Integration stage.
c. **Validation and Output:** After passing through Data Validation, the system classifies the trauma level into Low, Medium, or High categories. The process concludes with the Display of Diagnostic Results, which the user then receives as a Diagnosis Report.

2.4 Evaluation Metrics

Performance evaluation is conducted comparatively to measure the effectiveness of the developed hybrid system. This evaluation process compares the model's classification performance under two primary conditions: before and after the implementation of the SMOTE technique. This testing is crucial to validate whether data balancing can reduce model bias and enhance generalization capabilities in identifying minority classes among PTSD sufferers [18].

The evaluation metrics used include Accuracy, Precision, Recall, and F1-Score. In the context of mental health diagnosis, using Accuracy alone is often misleading when the dataset is imbalanced. Therefore, Recall becomes a priority metric to minimize false negatives (undetected trauma sufferers), while the F1-Score is used as a measure of the balance between the model's sensitivity and precision. This clinically-oriented evaluation approach is essential to ensure the safety and effectiveness of diagnoses

within a healthcare service environment [19]. The use of these comprehensive metrics aims to guarantee that the system possesses significantly better reliability compared to the Keyword Matching methods used in previous research [6]. In contrast to keyword matching, which is rigid and heavily dependent on the presence of specific terms, this hybrid system is evaluated on its ability to understand broader and more dynamic narrative contexts through a probabilistic Machine Learning approach [20].

3. RESULTS AND DISCUSSION

Following the execution of the methodology, this research has produced a hybrid system that integrates expert logic with machine learning algorithms. This section presents the results of the system implementation along with an analysis of the experimental performance. The discussion focuses on the system's practical operations, the accuracy levels achieved, and a comparison with previous studies to highlight the novelty of the proposed approach. The results of this study not only demonstrate the effectiveness of integrating Forward Chaining and Random Forest but also provide an overview of how a hybrid approach can overcome the limitations of pure expert systems in handling complex narrative data. The implemented hybrid approach illustrates how the integration of expert logic and machine learning can enhance system reliability when facing variations in user narratives.

3.1 Hybrid System Implementation

This system is implemented as a hybrid solution that integrates rule-based intelligence and machine learning. Qualitatively, Forward Chaining serves as a clinical logic filter, ensuring that every output has a standardized diagnostic foundation aligned with expert criteria. Meanwhile, Random Forest functions to handle linguistic ambiguity and variance within user narratives that are not captured by rigid rules.

This integration is manifested in a Hybrid Inference Engine. If the Forward Chaining process encounters non-linear or unstructured data patterns, the SMOTE-optimized Random Forest model provides additional predictive weighting to determine the final classification [21]. Theoretically, this approach enhances system reliability in providing more personalized and dynamic diagnoses. [22].

3.2 Performance Analysis and Experimental Comparison

Quantitative testing was conducted to measure the effectiveness of the hybrid system following the data preprocessing and class balancing stages. The experimental results demonstrate that the integration of Random Forest, supported by the SMOTE technique, provides a significant performance enhancement across all evaluation metrics. To validate the superiority of the proposed method, a comparison with several previous studies was performed, as presented in Table 1.

Table 1. Performance Comparison of the Model with Previous Studies

Author(s)	Method	Accuracy	Description
[23]	Random Forest	88,8%	Focuses on predicting common mental disorders (Depression/Anxiety) among youth.
[24]	ExtraTreesClassifier	88,8%	Utilizes behavioral features and symptoms for mental disorder classification.
[25]	C4.5 + feature BPSO	98,2%	BPSO integration enhances feature selection and C4.5 model efficiency. Relevant as a benchmark for feature optimization techniques in rule-based expert systems.
This research	Hybrid (FC + RF + SMOTE)	99,2%	Classification of trauma levels (Low, Medium, High) with data optimization.

Based on Table 1, the achieved accuracy of 99.2% demonstrates that this hybrid system possesses exceptionally high reliability in recognizing symptom patterns of PTSD sufferers compared to other single-method approaches. This achievement surpasses the research results of [23], [24] which recorded

an accuracy of 88.8%. Although the research in the journal [25] achieved 98.2% through BPSO optimization, the proposed hybrid system remains superior in the aspect of classifying more complex trauma severity levels (Low, Medium, High).

On the other hand, a Recall value of 73% provides a more specific overview of the system's ability to identify trauma cases amidst the ambiguity of the sufferers' narratives. In the mental health domain, achieving Recall at this level indicates that the system is capable of recognizing the majority of severe trauma indications while simultaneously minimizing the risk of false negatives, a condition where trauma sufferers go undetected. Although there remains room for improvement regarding model sensitivity, these results prove that the hybrid approach is significantly more adaptive in handling complex narrative data compared to conventional methods.

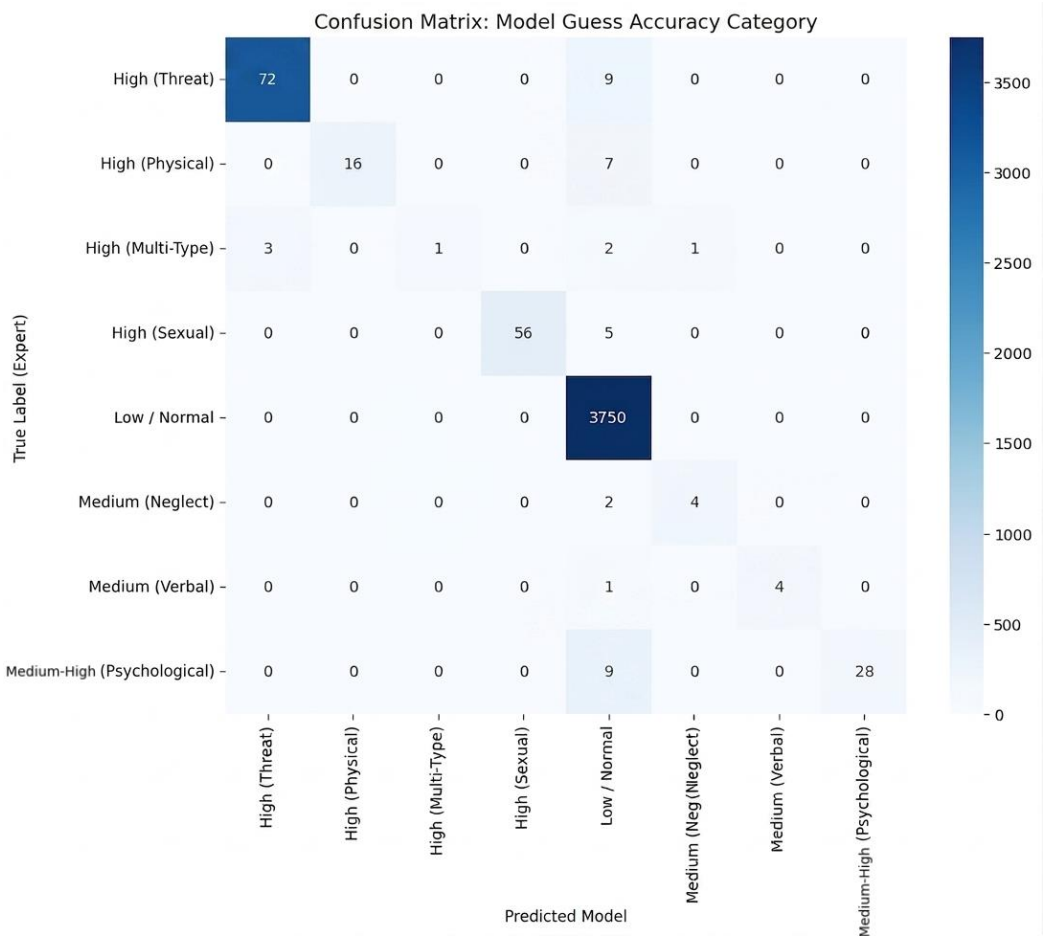


Figure 4. Confusion Matrix of PTSD Trauma Level Classification

To deepen the analysis of classification effectiveness across classes, the Confusion Matrix visualization is presented in Figure 4. The matrix demonstrates the model's robust discriminatory capability, particularly in the majority class 'Low/Normal' with 3,750 correct predictions. Furthermore, the model exhibits stable performance in identifying specific trauma categories, such as 'High (Threat)' with 72 true positives and 'High (Sexual)' with 56 true positives.

Although a very small classification error margin exists, it is insignificant compared to the total dataset. These results prove that the implementation of SMOTE successfully addresses the class imbalance constraints frequently encountered in medical datasets. Consequently, the model maintains a fair assessment weight across all trauma categories, providing strong justification that the hybrid approach is superior in handling the narrative data of PTSD sufferers.

3.3 Perbandingan dengan penelitian Sebelumnya

To highlight the research novelty, a functional comparison was conducted between the proposed hybrid system and previous rule-based trauma detection systems [6]. Given that previous research did not include quantitative testing, the comparison is focused on the enhancement of methodological capabilities and the depth of the system's output.

Table 2. Functional and Methodological Comparison

Comparison Criteria	Previous Studies [6]	This Research
Primary Method	Rule-Based (Keyword Matching).	Hybrid (Forward Chaining and Random Forest).
Analysis Process	Identification based on static keywords.	Integration of clinical logic and narrative pattern learning.
Data Handling	No class imbalance handling.	SMOTE optimization to balance minority classes.
System Output	Binary: Yes/No (detected or not detected).	Multi-level classification: Low, Medium, High (PTSD trauma levels).
Evaluation & Validation	No quantitative accuracy testing.	Performance testing using Accuracy, Precision, Recall, and F1-Score for system reliability validation.
Predictive Capability	Limited to keyword matching.	Capable of predicting complex and contextual PTSD symptom patterns.

Theoretically, the transition from binary identification to a three-level trauma classification provides significant practical advantages in mental health services. This hybrid system no longer relies solely on the occurrence of specific keywords; instead, it is capable of understanding the emotional context and linguistic patterns of users through the Random Forest probabilistic model. The implementation of SMOTE also ensures that the system remains sensitive to indications of severe trauma, even with limited data. This guarantees that the system is more robust against variations in PTSD sufferers' narratives compared to single rule-based systems, which tend to be rigid and static [26].

4. CONCLUSION

This study has successfully developed a hybrid expert system for PTSD trauma level classification by integrating Forward Chaining and Random Forest methods. Based on the results and discussion, the following key points can be concluded:

1. Research Results: The hybrid system is capable of classifying PTSD trauma levels into three categories (Low, Medium, and High) with exceptional performance. Quantitative testing demonstrated an Accuracy of 99.02%, with a Precision of 97%, Recall of 73%, and an F1-Score of 80%.
2. System Strengths: The primary advantage of this system lies in its ability to handle user narrative ambiguity through a hybrid approach. The effective use of SMOTE addresses class imbalance within the medical dataset, resulting in high sensitivity (73% Recall) in detecting severe trauma sufferers—a feat previously difficult to achieve with conventional Keyword Matching methods.
3. System Limitations: Despite its high accuracy, the system currently relies on static datasets from public repositories. Furthermore, model performance in certain extremely minority symptom categories still shows lower Recall variations compared to majority classes, indicating the need for a more comprehensive rule-based approach for specific cases.
4. Future Work: For future research, it is recommended to integrate Deep Learning architectures, such as Transformers or BERT, to achieve a deeper understanding of narrative context. Additionally, expanding the system into a real-time mobile platform and integrating it with telemedicine services could be pursued to provide broader and faster access to mental health assistance for the public.

5. SUGGESTED

The following recommendations emphasize the directions for future development previously mentioned in the conclusion. The objective is to highlight the aspects that subsequent research should address to further refine PTSD detection systems:

1. Data Source Expansion: Future research is encouraged to utilize primary datasets derived from direct observations or real-time clinical interviews. This is intended to test the model's robustness against more dynamic variations in narrative language compared to static repository datasets.
2. Algorithmic Exploration: It is recommended to integrate advanced Deep Learning architectures, such as Bidirectional Encoder Representations from Transformers (BERT) or Long Short-Term Memory (LSTM). This integration aims to enhance contextual and semantic understanding of longer and more complex user narratives.
3. Pengembangan Platform: Subsequent researchers may implement this hybrid system into mobile-based applications or web services. These platforms should be integrated with data encryption features, considering the high sensitivity of mental health data for trauma sufferers.
4. Multimodal Feature Integration: It is suggested to incorporate multimodal features, such as speech-to-text or facial expression analysis, to enrich the parameters of clinical symptom indicators beyond narrative text inputs.

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