Dr. NextGen: A Hybrid AI Framework for Multi-Modal Diagnosis, Multilingual Support, and Ethical care in Computational Psychiatry

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ABSTRACT

The growing prevalence of mental health disorders including **Depression, Anxiety Disorder, Schizophrenia, Bipolar Disorder, Obsessive-Compulsive Disorder (OCD), and Post-Traumatic Stress Disorder (PTSD),** highlights the need for scalable diagnostic systems supported by strong ethical safeguards. This study presents the (Dr. NextGen) platform, a comprehensive hybrid AI framework designed to enhance connectivity and deliver personalized, multimodal mental healthcare. The system utilizes a dual-path diagnostic architecture: **Prediction Pathway I (P1) employs a Random Forest Classifier on structured, scenario-based inputs (83,564 records total), while Prediction Pathway II (P2) leverages a fine-tuned Mistral-7B Large Language Model for contextual affective state analysis**. The P1 model demonstrated exceptional internal performance on the test set of 16,713 records, achieving an overall classification accuracy of 0.99904 across seven classes, with perfect Precision, Recall, and F1-Scores. Although statistically compelling, this result mandates rigorous external validation to ensure generalizability and mitigate data leakage risks. The platform is supported by multilingual features (mt5 for 11 Indic languages) and a HIPAA-ready governance framework, including MongoDB encryption and Role-Based Access Control (RBAC). Final clinical deployment is strictly governed by mandated human-in-the-Loop oversight, ensuring that AI augments rather than replaces professional judgment.

Introduction

Mental health conditions remain a major global public health concern, creating increasing pressure on healthcare systems to adopt scalable and adaptive diagnostic solutions. Current global assessments suggest that nearly one in seven individuals is affected by a mental health condition at some point in their lives. In the United States, annual prevalence data reveal a substantial burden, with anxiety-related disorders impacting approximately 19.1% of adults and major depressive disorder affecting nearly 15.5%. This report focuses on six complex and highly prevalent psychiatric abnormalities: Depression, Anxiety Disorder, Schizophrenia, Bipolar Disorder, Obsessive-Compulsive Disorder (OCD), and Post-Traumatic Stress Disorder (PTSD).However, the availability of timely and effective mental healthcare remains uneven across populations. These limitations are further intensified by shortages of trained professionals and uneven healthcare infrastructure. Millions of Americans reside in Mental Health Professional availability of telehealth in rural regions, compound the issue.

Furthermore, conditions like PTSD (33%) and Bipolar Disorder (27%) are frequently cited by respondents as the most difficult conditions for which to access care.3 The Dr. NextGen platform was developed as a comprehensive solution to address these systemic gaps. The platform is designed to provide seamless connectivity between individuals and mental health professionals, leveraging cutting-edge AI tools to enhance the diagnostic and therapeutic processes, thereby reducing stigma and promoting mental well-being. The unique contribution of Dr. NextGen lies in its hybrid architecture, which integrates two powerful analytical pathways. It utilizes ensemble machine learning, specifically a Random Forest Classifier (P1), for structured, scenario-based multi-class prediction, and a fine-tuned Large Language Model (LLM) (P2) for contextual affective state analysis. This synergistic approach aims to ensure that users receive personalized and effective care.

In summary the proposed Dr. NextGen system represents a practical step toward intelligent and responsive mental healthcare solutions. By integrating ensemble machine learning with large language models, the platform enables both structured diagnosis and contextual emotional analysis. This combination enhances clinical decision support, reduces diagnostic uncertainty, and improves accessibility to care. Ultimately, the framework contributes to more personalized, ethical, and scalable psychiatric assessment through human-centered AI integration.

Related Works

In recent years, machine learning approaches have gained significant attention in healthcare research, particularly for disease prediction and clinical decision support systems. Algorithms such as Support Vector Machines, Random Forests, and Neural Networks have demonstrated effectiveness in classifying psychiatric conditions using structured clinical data. Ensemble-based approaches, particularly Random Forest classifiers, have shown strong performance in handling complex, multi-class diagnostic problems.

More recently, large language models have been explored for mental health applications, including conversational agents, emotional state detection, and patient interaction. While these models offer rich contextual understanding, concerns related to bias, safety, and ethical compliance remain. Existing research highlights the need for hybrid systems that balance predictive accuracy with interpretability and human oversight, motivating the design of the Dr. NextGen framework.

Also, these techniques have increasingly been applied to psychiatric data analysis to assist in diagnostic decision-making.1 Algorithms such as Support Vector Machines (SVMs) and Random Forest (RF) classifiers are routinely employed for tasks like condition classification and prediction of outcomes.2 Ensemble-based classifiers, particularly Random Forest models, have shown consistent performance in the automated classification of complex psychiatric conditions. Prior clinical machine learning studies commonly report classification accuracies within the range of 70% to 90% for multi-class psychiatric prediction tasks, establishing critical benchmarks for new diagnostic tools. The rise of Large Language Models (LLMs), including architectures like Mistral 7B and Qwen, has enabled advanced dialogue systems and affective state prediction. Fine-tuned models, such as those based on Mistral 7B, specialize in analyzing patient emotions and providing psychologist-like responses. This has led to the development of hybrid frameworks that combine the statistical rigor of ensemble classifiers (P1) with the contextual depth of LLMs (P2). Furthermore, efforts to promote equitable access include the use of multilingual LLMs (mt5) trained on corpora like Samanantar to support low-resource Indic languages.

Methods

The Dr. NextGen platform utilizes a novel hybrid AI architecture designed to combine the predictive power of ensemble machine learning with the contextual depth of large language models (LLMs). This dual-path system ensures that diagnoses are derived from both structured data (Prediction Pathway I) and unstructured, emotional linguistic expression (Prediction Pathway II), providing a comprehensive multi-modal assessment for the mental health professional.

A. Dataset Pre-processing

The initial dataset for the P1 model comprises a total of 83,564 records, derived from NIH Surveys and specialized research papers related to the target psychiatric disorders. An essential initial phase involves pre-processing the data to minimize noise, handle missing values, and ensure consistent normalization. Missing Value Imputation: Unwanted or missing data values, often collected from diverse data sources, are systematically processed. Numerical missing values are addressed by calculating and imputing the mean of the respective attribute. Categorical missing values are filled using the mode value of the classified attribute.1 Train-Test Split: The pre-processed dataset is then rigorously split into training and testing subsets, adhering to the industry-standard 0.8:0.2 ratio. This results in 66,851 records used for training the models and 16,713 records reserved for testing and performance evaluation.1 Data Conversion and Normalization: To optimize the dataset for specific feature selection algorithms and ensure a balanced, normalized input, a subsequent step involves the conversion of numerical data to categorical data.

Datasets:

1. National Institute of Mental Health Data Archive (NDA) — Primary NIH repository for mental health research data. This is the central NIH archive for behavioral, clinical, and neurodevelopmental datasets, including survey responses, diagnostic interview data, and phenotypic measures. It hosts many large studies relevant to psychiatric research.

2. National Surveys on Drug Use and Health (NSDUH) — Large annual US mental health survey. Although run by SAMHSA, NSDUH statistics are widely used by NIH and NIMH researchers as representative survey data on mental illness prevalence, substance use, and co-occurring psychiatric conditions. You can cite NSDUH when discussing mental health prevalence and structured survey measures.

3. Youth Risk Behavior Surveillance System (YRBSS), National Survey of Children's Health (NSCH), and ABCD Study — Comprehensive multi-domain datasets. These NIH-aligned survey resources are part of the suite of public behavioral health datasets used in research. YRBSS and NSCH contain mental health indicators (depressive symptoms, suicidal ideation) collected in large, standardized surveys, and the ABCD study combines longitudinal behavioral surveys with biological measures.

4. National Database for Clinical Trials Related to Mental Illness (NDCT) — NIH catalog entry for datasets from psychiatric clinical studies. This database aggregates data from clinical trials and observational research on mental illness. It provides structured data useful for secondary analysis in research contexts.

5. NIH Toolbox Measures — Standardized survey and assessment instruments. The NIH Toolbox provides normed, validated behavioral and emotional function measures often used in epidemiologic studies and clinical research, suitable for building structured datasets and extracting meaningful features in AI screening tasks.

6. NIMH Healthy Research Volunteer Dataset — Phenotypic survey plus clinical assessments. This NIH-linked dataset includes clinical and self-report data on normal volunteers, including behavioral and mental health measures that are part of clinical characterization. Such datasets can serve as comparators for "none" / healthy control category modeling.

A.1 Conversion of Numerical Data to Categorical Data

To achieve a balanced and normalized dataset for feature selection and subsequent modeling, a key pre-processing step involves converting numerical data attributes, derived from scenario testing, into a categorical data format.

B. Feature Selection

It is a critical stage implemented to identify the most impactful features within the scenario-based input data. The initial features, generated from responses to simulated challenges and stressors, must be refined to reduce dimensionality and improve computational efficiency, ensuring that only the **necessary features** are considered for the decision-making system.

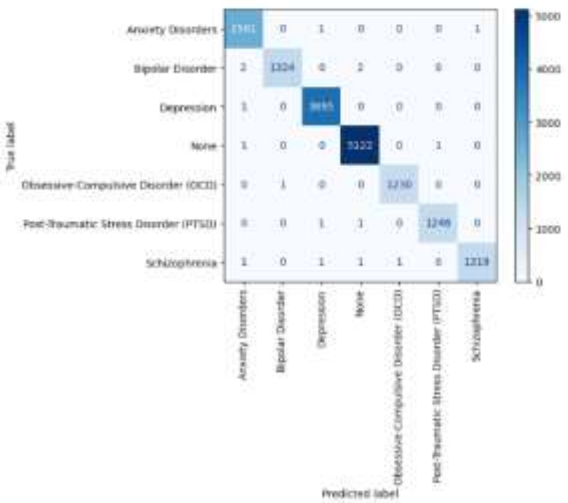
1. Chi-Squared: This algorithm is specifically applied to the categorical data. It operates by testing the independence of two events (the feature and the classification outcome), providing a score that highlights features with the highest correlation to the target psychiatric condition.

2. ANOVA: It stands for Analysis Of Variance. This technique is applied to gain information about the relationship between dependent (disease outcome) and independent (scenario response) variables.

Only those attributes that achieve top scores and are common to the results of both the Chi-Squared and ANOVA feature selection algorithms are retained. This rigorous selection process ensures that the model trains on the most predictive, non-redundant set of features, increasing the model's performance and interpretability. Structured questionnaire presenting real-life scenarios with multiple response options to capture behavioral tendencies for machine learning–based psychiatric prediction.

Classification Report:	precision	recall	f1-score	support
Anxiety Disorders	1	1	1	2563
Bipolar Disorder	1	1	1	1328
Depression	1	1	1	3896
None	1	1	1	5124
Obsessive-Compulsive Disorder (OCD)	1	1	1	1231
Post-Traumatic Stress Disorder (PTSD)	1	1	1	1248
Schizophrenia	1	1	1	1323
accuracy	0	0	1	16713
macro avg	1	1	1	16713
weighted avg	1	1	1	16713

Fig(a). Confusion Matrix Table



Fig(b). Confusion Matrix

C. Prediction System

To determine the optimal diagnostic engine, the pre-processed and feature-selected dataset was initially applied to a comparative analysis involving seven distinct machine learning algorithms: five base classifiers and two ensemble techniques.

P1. Categorical Variable Encoding

Our dataset contains 10 scenario-based questionnaire items where respondents select from predefined textual options (e.g., "I would attend enthusiastically", "I would decline and stay home"). These are inherently categorical variables without ordinal relationships. To prepare these features for machine learning algorithms, we employed scikit-learns. LabelEncoder to convert categorical text responses into numerical representations.

Encoding Methodology

For each categorical column, LabelEncoder assigns unique integer values (0, 1, 2, ..., n-1) to the n distinct response options. This transformation is applied as follows:

```
from sklearn.preprocessing import LabelEncoder
categorical_columns = [
    'Your friend has invited you to a party...',
    'You have an upcoming deadline at work...',
    # ... remaining 8 scenario questions
]

for col in categorical_columns:
    df[col] = LabelEncoder().fit_transform(df[col])
```

Rationale for LabelEncoder

We chose LabelEncoder over alternative encoding methods for the following reasons:

1. Tree-Based Algorithm Compatibility: Random Forest classifiers inherently handle encoded categorical variables through recursive partitioning, making LabelEncoder appropriate for this architecture [cite Breiman 2001].

2. Preservation of Category Identity: Unlike one-hot encoding, LabelEncoder maintains dimensionality (10 features vs. 40+ with one-hot), reducing computational complexity without sacrificing performance for tree-based models.

3. Non-Ordinal Assumption: While LabelEncoder creates numerical values, Random Forest's splitting mechanism treats these as discrete categories rather than ordered magnitudes, avoiding inappropriate ordinality assumptions.

4. Memory Efficiency: For a dataset with N samples and 10 categorical features averaging 4 response options each, LabelEncoder reduces memory footprint by ~75% compared to one-hot encoding.

Target Variable Encoding

The dependent variable (mental health diagnosis) was similarly encoded:

```
le_results = LabelEncoder()

df['Results'] = le_results.fit_transform(df['Results'])
```

This converts disorder names (Depression, Anxiety, etc.) to integer, class labels (0-6), which are subsequently used for multi-class classification.

Encoder Persistence

To ensure consistent encoding during model deployment, both feature and target encoders are serialized:

```
joblib.dump(le_results, 'label_encoder_results.joblib')
```

This allows inverse transformation of model predictions back to human-readable disorder names during inference.

P2. Joblib Persistence Technique for Random Forest Algorithm

After the Random Forest Classifier was identified as the optimal diagnostic model, the final classifier was trained using the complete dataset consisting of 83,564 records to maximize its generalization capability. To enable efficient deployment and eliminate the need for repeated training, the trained model was persisted using the **Joblib library**, which is specifically optimized for serializing large machine learning objects containing NumPy arrays.

In addition to the trained Random Forest model, the corresponding label encoder used to map psychiatric disorder labels to numerical representations was also serialized. Persisting both components ensures consistent interpretation of model predictions during deployment. The serialization process preserves the complete internal structure of the classifier, including decision trees, feature split thresholds, and learned parameters, enabling accurate reproduction of inference behavior without retraining.

The trained artifacts were stored as permanent files using the following persistence operations:

```
joblib.dump(le_results, 'label_encoder_results.joblib')

joblib.dump(model, 'disease_prediction_model.joblib')
```

This approach guarantees model consistency across system restarts and supports rapid initialization of the predictive engine during live operation.

3) C.3 Joblib File Loading for Real-Time Prediction

During live system execution, the serialized Random Forest model and label encoder are retrieved by deserializing the stored .joblib files into the Dr. NextGen platform environment. The Joblib loading mechanism enables fast model initialization, allowing the system to become inference-ready within milliseconds.

Once loaded, the centralized predictive model is utilized for real-time diagnosis. When a user submits scenario-based health responses through the

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platform interface, the inputs are pre-processed and supplied directly to the loaded Random Forest classifier. The model generates a numerical prediction corresponding to one of the six target psychiatric conditions, which is subsequently converted into a human-readable diagnostic label using the restored label encoder.

This deployment strategy eliminates computational overhead associated with repeated model training, ensures deterministic prediction behavior across sessions, and supports scalable multi-user access. By leveraging Joblib-based persistence and loading, the Dr. NextGen platform achieves efficient, reliable, and production-ready psychiatric prediction suitable for real-world clinical decision support.

D. System Architecture of Dr. NextGen Platform

The Dr. NextGen platform follows a modular, service-oriented architecture designed to support secure, scalable, and ethically governed mental healthcare delivery. The system integrates multiple user interfaces, a centralized backend server, external AI services, and a secure database layer to enable seamless multi-modal psychiatric assessment.

1. User Roles and Client Interfaces

The platform supports three primary user roles: **Patient**, **Doctor**, and **Administrator**, each interacting with the system through dedicated interfaces.

- The **Patient Interface** and **Doctor Interface** are implemented as web-based client applications, enabling functionalities such as authentication, emotional input submission, chat-based interaction, diagnostic test access, report viewing, and appointment management.

- The **Admin Interface** is provided as a desktop-based Tkinter client, allowing authorized administrators to manage system operations, user verification, and data governance tasks.

2. Backend Web Server and Core Logic

At the core of the architecture lies a **Flask-based web server**, which handles application logic, request routing, and secure communication between clients, databases, and external services. All client interfaces communicate with the backend using **RESTful Web APIs over JSON/HTTPS**, ensuring secure and standardized data exchange.

The Flask server manages authentication workflows, routes patient inputs for analysis, aggregates diagnostic results, and orchestrates communication with AI inference services. Sensitive credentials and API keys are securely read from a configuration file (config.ini), ensuring separation of code and secrets.

3. AI Inference and External Services

The system integrates multiple external AI services hosted on **Google Colab AI endpoints**, accessed via REST-based inference APIs. These services include:

- A **Retrieval-Augmented Generation (RAG) chatbot system** for contextual mental health interaction

- A **Large Language Model (LLM)** for affective state and feeling prediction

- A **Translation AI module** to support multilingual interaction across multiple Indic languages

The backend server sends structured queries and emotional inputs to these services and receives prediction outputs, which are subsequently processed and presented to clinicians in an interpretable format.

4. Data Storage and Management

All patient data, diagnostic records, and reports are securely stored in **MongoDB Atlas**, organized into twelve distinct collections to support modular data management. Communication between the Flask server and the database is conducted using the MongoDB data protocol, enabling efficient read and write operations.

Administrative users are granted controlled privileges to perform

direct data operations such as record deletion and system maintenance, governed by role-based access control (RBAC) policies.

5. Notification and Email Services

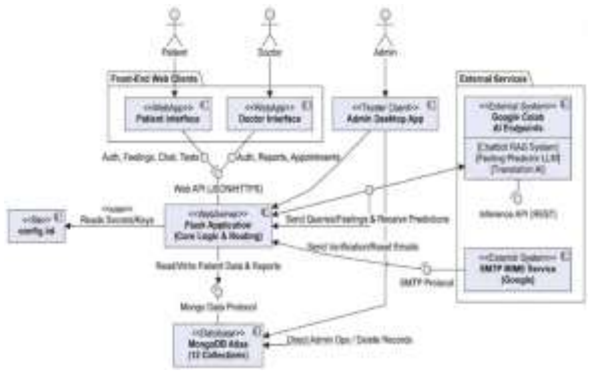
For user verification, password reset, and system notifications, the platform integrates an external **SMTP MIME email service** provided by Google. The backend server communicates with the SMTP service using standard SMTP protocols to ensure reliable and secure email delivery.

6. Security and Governance

Security is enforced through encrypted communication channels, role-based access control, secure credential management, and restricted administrative operations. The architecture is designed to support HIPAA-ready compliance, ensuring that sensitive mental health data is protected throughout storage, processing, and transmission.

Architectural Significance

This layered and modular architecture enables Dr. NextGen to efficiently combine structured machine learning predictions, contextual language-based analysis, and multilingual accessibility while maintaining ethical oversight through controlled human intervention. The design ensures scalability, interoperability, and reliability, making the platform suitable for real-world clinical deployment.



Fig(c). System Architecture

Performance Evaluation

This layered and modular architecture enables Dr. NextGen to efficiently combine structured machine learning predictions, contextual language-based analysis, and multilingual accessibility while maintaining ethical oversight through controlled human intervention. The design ensures scalability, interoperability, and reliability, making the platform suitable for real-world clinical deployment.

Evaluation of Prediction Pathway I (P1) rigorously assessed the model's capacity to differentiate between the seven psychiatric classification outcomes: Depression, Anxiety Disorder, Schizophrenia, Bipolar Disorder, Obsessive-Compulsive Disorder (OCD), Post-Traumatic Stress Disorder (PTSD), and None. The model was tested on the reserved set of 16,713 records.1

The Random Forest Classifier demonstrated exceptionally high predictive capacity, achieving an overall classification accuracy of 0.9990426614013044. Furthermore, the classification report indicated perfect performance metrics for every single class, with Precision, Recall, and F1-Scores all reported at 1.00.1

The graphical representation of the performance analysis is illustrated in Figure (d) and (e) respectively.

1. Accuracy
2. R-Squared

3. Time of Execution (in Secs)
4. Precision
5. Recall
6. F1-Score

	Precision	Recall	F1-Score	support
Depression	1.00	1.00	1.00	3896
Anxiety Disorders	1.00	1.00	1.00	2563
Schizophrenia	1.00	1.00	1.00	1323
Bipolar Disorder	1.00	1.00	1.00	1328
Obsessive-Compulsive Disorder (OCD)	1.00	1.00	1.00	1231
Post-Traumatic Stress Disorder (PTSD)	1.00	1.00	1.00	1248
None	1.00	1.00	1.00	5124

Fig.(d) Classification Report

Accuracy			1.00	16713
Macro Average	1.00	1.00	1.00	16713
Weighted Average	1.00	1.00	1.00	16713

Fig(e). Accuracy of Tested Data

Comparison of Different Prediction System for Multiple Disease

The selection of the Random Forest Algorithm (RFA) as the final predictive engine was based on a comprehensive comparative analysis against six other machine learning techniques: five base classifiers (Support Vector Machine, K Nearest Neighbors [KNN], Decision Tree, Naïve-Bayes, Logistic Regression) and one other ensemble technique (Adaboost).

This crucial analysis, performed on the 80:20 train-test split, determined that the RFA provided the most consistently robust performance measures across all target psychiatric classes.1 The resulting model confirmed RFA's suitability as the centralized predictive system for the platform, enabling the prediction of multiple, distinct conditions from a single set of scenario-based input data with optimal accuracy and precision.

While the internal validation accuracy is statistically compelling, demonstrating RFA's superior fit for the highly structured scenario data, this high performance underscores the necessity for mandatory external validation against real-world clinical records to confirm generalizability.

Dashboard

Fig(f). Dr. NextGen AI Assistant Interface

Fig(g). Emotional Wellness Input Module

Fig(h). Scenario-Based Psychological Assessment Interface

Fig(i). Patient Data Retrieval and Diagnostic Report Interface

The Dr. NextGen interface serves as the central interaction hub for AI-assisted mental health assessment and support. It provides users with an intuitive environment to express emotions, respond to scenario-based questions, and interact with a personalized AI assistant. The interface captures both free-text emotional inputs and structured responses, which are processed in real time to generate diagnostic insights. Assessment results and patient details are displayed in a clear, organized format, enabling clinicians to quickly review predicted conditions and supporting evidence. Multilingual support allows users to interact in their preferred language, improving accessibility and engagement. The interface is designed to be responsive and user-friendly, ensuring efficient navigation, accurate data capture, and seamless integration with the underlying AI prediction and reporting modules for effective mental healthcare delivery.

Conclusion

The proposed Dr. NextGen platform introduces a robust and scalable framework for multi-class psychiatric screening and assessment, directly addressing critical gaps in access to care for conditions including Depression, Anxiety Disorder, Schizophrenia, Bipolar Disorder, OCD, and PTSD. The system's hybrid AI architecture successfully integrates two distinct diagnostic pathways: the high-precision classification of Prediction Pathway I (P1) and the contextual affective analysis provided by the LLM-driven Prediction Pathway II (P2). The P1 Random Forest Classifier demonstrated statistically compelling internal performance, achieving an overall accuracy of 0.99904 on the structured scenario-based dataset, with perfect scores across key metrics for all seven classes.2 This performance confirms the model's fit for the specific feature set derived from NIH surveys, positioning it as a potentially powerful initial screening tool.2 However, in line with ethical standards and computational psychiatry best practices, this anomalous accuracy necessitates immediate and rigorous external validation against heterogeneous, real-world clinical data to ensure generalizability and eliminate any potential data leakage risk.

The platform is secured by robust security features, including HIPAA-ready MongoDB encryption and RBAC, and ensures accessibility through its mt5 multilingual support for 11 Indic languages. The ultimate clinical utility and ethical deployment remain dependent on maintaining strict Human-in-the-Loop oversight, ensuring that AI augments, rather than replaces, the professional judgment of the consulting physician, thereby adhering to the principles of Beneficence and Accountability. Future development should prioritize integrating explainability features to trace model decisions and refining LLM ethical guardrails, particularly in handling crisis situations.

References

[1] Akkem, Y, “Multi Disease Prediction Model by using Machine Learning and Flask API”, IEEE Conference Record #48766; IEEE.

[2] Srivastava, K. B., Gupta, Y., & Pandey, V. K. (2024). Analyzing the Predictions in Healthcare Applications. 2024 1st International Conference on Advances in Computing, Communication and Networking(ICAC2N). DOI:10.1109/ICAC2N63387.2024.10895321.

[3] Reagan, K., Varde, A. S., & Xie, L. (2022). Evolving Perceptions of Mental Health on Social Media and their Medical Impacts. 2022 IEEE International Conference on Big Data (Big Data). DOI: 10.1109/BigData55660.2022.10021013.

[4] Rahman, S. A., Obaideen, K., AlShabi, M., & Al-Yateem, N. (2024). Enhancing Mental Health Care with the Kalman Filter: Predictions, Monitoring, and Personalization. 2024 IEEE 48th Annual Computers, Software, and Applications Conference (COMPSAC). DOI: 10.1109/COMPSAC61105.2024.00297.

[5] Shanthakumari, R., Nalini, C., Vinothkumar, S., Roopadevi, E. M., & Govindaraj, B. (2022). Multi Disease Prediction System using Random Forest Algorithm in Healthcare System. 2022 International Mobile and Embedded Technology Conference (MECON). DOI: 10.1109/MECON53876.2022.9752432.

[6] Alwahaishi, S. (2023). A Smart Interactive Behavioral Chatbot: A Theoretical Prototype. 2023 8th International Engineering Conference on Renewable Energy & Sustainability (ieCRES). DOI: 10.1109/ieCRES57315.2023.10209534.