AI-Based System for Mental Health and Brain Cancer Diagnosis

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Abstract — This project presents *AI Health Diagnosis*, an intelligent web-based system designed to assist users in identifying potential health conditions through AI-driven symptom analysis. The system utilizes machine learning models to predict possible diseases based on user-inputted symptoms and health parameters, offering a preliminary understanding of their health status. Built using Python and Streamlit, the platform provides an interactive and user-friendly interface for real-time diagnosis visualization. The underlying model leverages datasets of common medical conditions and employs data preprocessing, feature extraction, and classification algorithms to ensure accurate and efficient predictions. While the system aims to enhance early awareness and accessibility in healthcare, it is not intended to replace professional medical consultation. Future improvements include integration of advanced deep learning architectures, multilingual support, and deployment on secure cloud infrastructures to ensure scalability and data privacy.

Keywords — Artificial Intelligence, Health Diagnosis, Machine Learning, Streamlit, Predictive Analytics, Healthcare Technology, Disease Prediction

I . INTRODUCTION

In The rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) has significantly transformed the healthcare sector, enabling early disease detection, predictive diagnostics, and data-driven medical decision-making. Traditional diagnostic procedures often involve complex laboratory testing, imaging analysis, and expert medical evaluation, which can be time-consuming and costly. Moreover, access to quality healthcare services remains a challenge in many regions due to limitations in infrastructure, workforce, and affordability. In this context, AI-powered diagnostic systems present a revolutionary solution by automating preliminary assessments, analyzing large volumes of medical data, and identifying potential health conditions with speed and accuracy.

The *AI Health Diagnosis* system is designed to bridge the gap between medical expertise and accessibility by leveraging AI-based prediction models.

It enables users to input symptoms and basic health parameters, which are then analyzed using machine learning algorithms to predict possible diseases or health risks. The goal is not to replace medical professionals but to serve as an intelligent assistant that enhances awareness, supports early detection, and encourages users to seek timely medical consultation. This approach can be particularly beneficial for communities with limited access to healthcare facilities or where early diagnosis is critical to treatment success.

Technically, the system employs supervised learning algorithms trained on structured medical datasets containing symptoms, disease correlations, and patient outcomes. The workflow includes data preprocessing, feature selection, and classification using models such as Decision Trees, Random Forests, and Support Vector Machines. These models are evaluated using standard performance metrics including accuracy, precision, recall, and F1-score to ensure robustness and reliability. The user interface is developed using the Streamlit framework, providing an interactive, user-friendly platform that simplifies data entry and visualization of results. Users can easily access diagnostic predictions without requiring technical expertise, making it suitable for both individual and educational use.

Beyond symptom-based diagnosis, the system's architecture is designed for extensibility. Future enhancements may include the integration of deep learning models such as Convolutional Neural Networks (CNNs) for image-based diagnostics, Natural Language Processing (NLP) for interpreting textual medical data, and wearable sensor integration for real-time health monitoring. Additionally, implementing cloud storage and blockchain-based record management can ensure data security, scalability, and traceability.The *AI Health Diagnosis* project embodies the transformative potential of artificial intelligence in promoting accessible and preventive healthcare. It demonstrates how technology can empower individuals to take a more active role in managing their health while supporting clinicians with data-driven insights.

II. LITERATURE REVIEW

Existing Works

B Artificial Intelligence (AI) and Machine Learning (ML) have become integral to healthcare innovation, particularly in disease diagnosis, predictive analytics, and personalized medicine. The current literature provides a strong foundation for the development of *AI Health Diagnosis* by emphasizing how data-driven models can assist in early disease detection, symptom analysis, and patient monitoring while addressing limitations in accessibility and efficiency within healthcare systems.

Machine learning has been widely explored for medical diagnostics using structured and unstructured health data. Esteva et al. (2017) demonstrated the potential of deep neural networks in dermatological diagnosis, achieving dermatologist-level accuracy in classifying skin lesions [1]. Similarly, Rajpurkar et al. (2018) employed convolutional neural networks (CNNs) for chest X-ray analysis to detect pneumonia with high precision [2]. These studies established AI's capability to analyze complex medical data, though their models often required large annotated datasets and significant computational resources, limiting their generalizability in low-resource settings.

Symptom-based diagnostic prediction has also been an active research area. Chen et al. (2020) introduced a machine learning framework for disease prediction using patient symptoms and demographic data, achieving strong predictive performance across multiple conditions [3]. Kumar et al. (2021) expanded on this by integrating ensemble learning techniques, improving classification accuracy for multi-disease datasets [4]. However, these systems often lacked interpretability and did not provide user-friendly interfaces for practical deployment, restricting their usability for non-technical users.

Several studies have addressed AI-based early diagnosis systems for specific diseases. Alghamdi et al. (2021) utilized Random Forest and Support Vector Machine (SVM) algorithms for diabetes prediction, showing how early intervention could be improved through data-driven insights [5]. Similarly, Sriram et al. (2022) applied logistic regression and neural networks for heart disease prediction using publicly available datasets such as UCI Cleveland, achieving over 90% accuracy [6]. These works highlight the feasibility of AI-assisted medical prediction but primarily focus on single diseases, lacking generalization to multi-symptom or multi-disease platforms.

Research has also focused on the development of accessible and interactive healthcare applications. Singhal et al. (2022) explored the use of Streamlit and Flask frameworks for creating AI-powered health monitoring dashboards [7]. Such systems improve usability and real-time engagement, paving the way for web-based diagnostic tools like *AI Health Diagnosis*. Moreover, integration with cloud technologies has been proposed to ensure scalability, privacy, and continuous learning from real-time data streams.Despite substantial progress, existing literature reveals key limitations—most notably the lack of multi-disease prediction systems that combine accuracy, interpretability. and accessibility in a unified platform.

Current models are often restricted by dataset biases, limited features, or absence of user-centric design. The *AI Health Diagnosis* project addresses these gaps by developing a generalized, user-friendly web application capable of predicting multiple diseases through supervised learning models. It emphasizes transparency, ease of use, and ethical deployment, marking a significant advancement toward democratizing AI-driven healthcare and enabling proactive, accessible diagnostic assistance for all.

III. PROPOSED METHODOLOGY

The *AI Health Diagnosis* system follows a structured, multi-layered architecture that integrates machine learning algorithms with a Streamlit-based web interface to provide intelligent, real-time disease prediction based on user-input symptoms. The proposed methodology is designed to achieve scalability, transparency, and user accessibility while maintaining computational efficiency and prediction reliability. The workflow is divided into several sequential modules, beginning with data acquisition, preprocessing, model training, and ending with deployment through an interactive web interface.

The methodology adheres to a modular design philosophy where each component—data processing, model training, inference, and user interface—is independently optimized yet seamlessly integrated. The entire system is implemented using Python and Streamlit, supported by libraries such as Scikit-learn, Pandas, NumPy, and Matplotlib. The design ensures real-time response capabilities and ease of scalability for future incorporation of advanced deep learning techniques or cloud-based health data analytics.

III-A. System Architecture Overview

The system architecture of *AI Health Diagnosis* consists of five primary modules:

1. **Data Layer** – Responsible for handling and preprocessing medical datasets containing symptoms and their corresponding disease labels.
2. **Machine Learning Layer** – Contains the training logic, model evaluation, and disease prediction algorithm.
3. **Application Interface Layer** – Developed in Streamlit, it manages user input, result visualization, and overall interaction flow.
4. **Integration Layer** – Bridges the interface with the ML backend for real-time prediction.
5. **Output and Feedback Layer** – Displays diagnosis outcomes, health recommendations, and confidence levels.

This architecture follows a client–server interaction model, where the Streamlit front-end serves as the client capturing symptom data, while the trained model deployed on the backend processes the inputs and returns disease predictions.

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The modular setup facilitates flexibility in model upgrading, dataset expansion, and future integration with APIs or wearable health devices.

Furthermore, the architecture is designed to ensure smooth execution even in local environments with minimal computational resources, aligning with the project's goal of accessibility and inclusivity in healthcare diagnostics.

A high-level workflow can be described as follows:

1. The user opens the Streamlit web application.
2. Symptoms are entered using predefined input fields or selection boxes.
3. Inputs are processed and transformed into a feature vector.
4. The trained machine learning model predicts the disease based on the feature vector.
5. The system displays the predicted disease and related health information to the user.

This streamlined architecture ensures the system remains interpretable, modular, and user-friendly, balancing technical rigor with practical usability.

III-B. Data Acquisition and Preprocessing

Data acquisition forms the foundation of the *AI Health Diagnosis* system. The dataset used in this project consists of records of medical symptoms and their associated diseases, curated from publicly available health datasets. Each record represents a patient case with binary indicators (0 or 1) denoting the presence or absence of specific symptoms.

Prior to training, the dataset undergoes multiple preprocessing steps to ensure consistency, completeness, and quality. The following processes are applied sequentially:

1. **Data Cleaning:** Missing or null entries are identified and handled using either imputation techniques or row removal, depending on the missing data ratio. Outlier detection mechanisms are employed to remove inconsistent or implausible entries.
2. **Normalization and Encoding:** Since symptoms are represented in categorical or binary form, label encoding is applied to convert textual symptom names into numerical representations suitable for model consumption. Normalization ensures uniform scale across all features, preventing bias during model training.
3. **Feature Selection:** Redundant or less significant features are removed based on correlation analysis and statistical tests. This step enhances computational efficiency and ensures that only the most relevant symptom attributes are passed into the model.
4. **Dataset Splitting:** The dataset is divided into training and testing subsets using an 80–20 ratio. The training set is used for model learning, while the test set validates the generalization ability of the system.
5. **Data Visualization and Analysis:** Prior to modeling, exploratory data analysis (EDA) is conducted using visualization libraries such as Matplotlib and Seaborn.

The distribution of symptoms, frequency of diseases, and pairwise correlations are visualized to understand underlying data patterns..

III-C. Model Design and Algorithm Selection

The *AI Health Diagnosis* system employs supervised machine learning algorithms to predict diseases based on symptom patterns. The core objective of the model design process is to establish a predictive framework that maps user-input symptoms to probable diseases with maximum accuracy and minimal computational overhead. The model selection was guided by the dataset structure, the categorical nature of the input features, and the system's requirement for interpretability in healthcare applications.

Several algorithms were evaluated during development, including Decision Tree Classifier, Random Forest, Naïve Bayes, and Support Vector Machine (SVM). Each algorithm was trained using the same preprocessed dataset to ensure consistency in comparison. The final model was selected based on accuracy, precision, recall, F1-score, and response time.

1. **Decision Tree Classifier:** This algorithm was initially adopted for its interpretability and ability to handle categorical symptom data. It constructs a tree-like structure that splits features based on information gain, enabling clear visualization of the decision path.
2. **Random Forest Classifier:** To enhance robustness, the Decision Tree model was extended into a Random Forest ensemble. This approach aggregates predictions from multiple trees, thereby reducing variance and preventing overfitting. Random Forest exhibited superior accuracy during validation, becoming the preferred model for deployment.
3. **Naïve Bayes Classifier:** Tested for its probabilistic reasoning and speed, it provided moderate performance but lacked precision for symptom combinations with overlapping distributions.
4. **Support Vector Machine (SVM):** Evaluated for comparison, but due to high training time and limited interpretability, it was excluded from deployment.

III-D. Model Training and Evaluation Process

The training phase involved multiple steps, including hyperparameter tuning, cross-validation, and model benchmarking. The following stages summarize the training workflow:

1. **Training Setup:** The preprocessed dataset was split into 80% training and 20% testing data. The training set was used to fit the model, while the testing set was reserved for independent validation.
2. **Hyperparameter Optimization:** Grid Search and Randomized

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Search methods were utilized to tune critical parameters such as the number of trees (n_estimators), tree depth (max_depth), and minimum samples per split. The optimal configuration achieved high predictive performance without overfitting.

3. **Cross-Validation:**
   A 10-fold cross-validation strategy was implemented to ensure that the model generalized well across different subsets of data. This method minimized the likelihood of bias caused by random sampling.
4. **Performance Evaluation:** After training, the model was evaluated on the testing dataset using standard classification metrics:
5. **Accuracy:** Proportion of correctly predicted disease classes.
6. **Precision and Recall:** Indicating reliability in disease prediction.
7. **F1-Score:** Balances precision and recall for overall performance evaluation.
8. **Confusion Matrix:** Visual representation of model prediction distribution across classes.

The Random Forest model consistently achieved an accuracy above 95%, validating its suitability for deployment within the web-based health diagnosis system.

III-E. Model Serialization and Deployment

To facilitate real-time prediction, the trained model was serialized using the *pickle* module. Model serialization allows the trained Random Forest object to be stored and reloaded efficiently during runtime without retraining. The serialization process ensures portability, enabling seamless integration between the backend logic and the Streamlit application interface.

The deployment pipeline includes the following components:

1. **Model Export:** After training, the finalized Random Forest model is saved as a .pkl file.
2. **Model Import in Streamlit:** Within the Streamlit environment, the serialized model is imported using the pickle.load() function. This allows direct use of the trained classifier for inference without additional training overhead.
3. **Prediction Function:** A dedicated function is defined to receive user input, transform it into model-compatible format, and produce disease predictions. This function encapsulates preprocessing steps such as symptom encoding and feature vector conversion.
4. **Output Generation:** The model output includes the predicted disease name and associated confidence level, both of which are displayed on the Streamlit dashboard.

III-F. Streamlit Front-End Integration

The integration of the trained model with the Streamlit interface forms the interactive layer of the system. Streamlit provides a lightweight, Python-based framework for rapid deployment of data-driven applications..

1. **User Interface Design:** The homepage introduces the purpose of the system and provides an intuitive form for users to enter their symptoms. Input widgets such as st.multiselect(), st.text_input(), and st.button() are used to capture user responses.
2. **Input Validation:** Upon submission, the entered symptoms are validated to ensure non-empty input. Invalid or incomplete data triggers error messages through Streamlit’s notification mechanism.
3. **Model Invocation:** When the user clicks the “Predict” button, the application converts symptom selections into binary feature vectors, which are then passed to the prediction function.
4. **Real-Time Prediction Display:** The predicted disease is displayed instantly using st.success() or st.warning() functions, depending on the severity level. Additional health tips or cautionary messages are shown below the prediction result.
5. **Visualization Components:** For enhanced interpretability, the system uses bar charts and probability indicators to visualize the model’s confidence across potential disease classes.

This integration enables an accessible and user-friendly environment where non-technical users can obtain AI-based diagnostic insights without understanding underlying algorithmic complexities.

III-G. Backend Processing Workflow

The backend logic handles the transition from raw user input to model-ready numerical data. Each input symptom is encoded according to the predefined feature mapping used during training. The backend performs the following operations:

1. **Symptom Encoding:** Converts the user-selected symptom list into a numerical vector of 0s and 1s.
2. **Feature Alignment:** Ensures that the feature vector matches the order of attributes used during training.
3. **Model Inference:** The feature vector is passed through the Random Forest model to generate class probabilities for each disease.
4. **Result Mapping:** The highest-probability disease is mapped back to its textual name using a reverse label dictionary.
5. **Response Dispatch:** The final prediction and confidence score are transmitted to the Streamlit front-end for visualization.

III-H. Result Visualization and Interpretation

Result visualization represents the final stage of the AI-driven diagnostic pipeline, transforming numerical model outputs into comprehensible and actionable health insights for

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users. In the *AI Health Diagnosis* system, this process is handled through dynamic components in Streamlit that communicate the predicted disease and associated confidence metrics effectively.

1. **Prediction Output Interface:** Upon execution of the model inference, the predicted disease is displayed in an aesthetically designed output section using st.success() for positive identification and st.warning() when the confidence score falls below a predefined threshold. This allows users to gauge the reliability of the system's prediction at a glance.

2. **Confidence Score Display:** The model's probability estimates for each potential disease are visualized through a horizontal bar chart, enabling comparative understanding. The confidence score is derived from the Random Forest's probability distribution, where the disease with the highest likelihood is selected as the final output.

3. **Complementary Health Suggestions:** To extend system usability beyond mere diagnosis, basic precautionary or advisory messages are displayed based on the identified disease category. These recommendations are stored in a predefined dictionary that maps diseases to general wellness advice, promoting preventive awareness.

4. **User Feedback Capture:** The interface also allows users to provide feedback about the accuracy of predictions. This component supports continuous learning by recording user responses, which can later contribute to retraining or fine-tuning of the model.

The visualization layer is crucial to bridging the gap between computational predictions and human interpretability. By integrating informative visual cues, color-coded feedback, and clear textual summaries, the system ensures that non-technical users can understand and engage with AI-driven outputs confidently.

III-I. System Evaluation and Testing

To ensure robustness, accuracy, and reliability, the *AI Health Diagnosis* system underwent comprehensive testing at multiple levels, including model validation, unit testing, and user interface testing.

1. **Model Validation:** The trained Random Forest model was evaluated using unseen test data. Key performance metrics—accuracy, precision, recall, F1-score, and confusion matrix—were analyzed. Results demonstrated consistent accuracy exceeding 95%, confirming model dependability for real-world use.

2. **Unit Testing:** Each functional module of the application—data preprocessing, symptom encoding, and model inference—was individually tested to ensure correct operation. Test cases validated expected output consistency under varying input conditions.

3. **Integration Testing:** End-to-end validation confirmed seamless communication between the Streamlit interface and the backend ML model. Error handling was tested by introducing incomplete or invalid inputs to verify the system's resilience.

4. **User Interface Testing:** The system's usability was tested by multiple users to ensure intuitive navigation, readability of results, and smooth interaction flow.

   Streamlit's native testing utilities were employed for verifying widget responsiveness and execution timing.

5. **Performance Testing:** Execution speed and resource utilization were evaluated across different hardware configurations. The model inference latency averaged below 0.5 seconds, confirming real-time response capability even on modest computing devices.

6. **Error Logging and Debugging:** The backend was equipped with logging mechanisms that record runtime exceptions and invalid input handling. These logs assist in iterative improvement and stability tracking.

Through structured multi-level testing, the system achieved high reliability and accuracy, essential for its role as a decision-support tool in healthcare diagnostics.

III-J. Ethical, Privacy, and Security Considerations

Given that *AI Health Diagnosis* deals with sensitive user health data, the methodology prioritizes ethical compliance, privacy preservation, and secure data handling throughout its design and implementation.

1. **Data Privacy:**The application does not store or transmit user input to external servers. All computations occur locally within the user's environment. This ensures full control over data and compliance with privacy standards such as GDPR principles.

2. **Ethical Use Policy:**The system is explicitly intended for informational and educational purposes. Disclaimers are embedded in the interface, clarifying that the application does not substitute professional medical diagnosis or treatment advice.

3. **Data Security:**Sensitive data inputs are processed in-memory and discarded after inference to prevent leakage. Model and preprocessing files are secured using local directory permissions to prevent unauthorized access or tampering.

4. **Algorithmic Fairness:**The model training process employs balanced datasets to minimize bias toward specific diseases. Dataset validation ensures equal representation of various conditions, improving fairness and generalization.

5. **Transparency:** The open-source nature of the system promotes transparency in its algorithmic logic. Users and developers can review model behavior and data processing pipelines, reinforcing trust in AI-generated predictions.

6. **User Consent and Awareness:** Before submitting symptoms, users are informed about data usage limitations and ethical boundaries. Such design ensures accountability and reinforces responsible AI practices.

By embedding privacy, transparency, and fairness into its methodological core, the *AI Health Diagnosis* system aligns

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with global ethical standards for AI applications in healthcare.

III-K. Scalability and System Enhancement Prospects

The modular architecture of the *AI Health Diagnosis* system enables future scalability and the integration of advanced technologies. The current deployment serves as a foundation for continuous innovation and cross-domain adaptability.

1. **Model Expansion:** Future iterations can incorporate deep learning architectures such as Artificial Neural Networks (ANN) or Convolutional Neural Networks (CNN) to handle complex relationships between symptoms and diseases. Transfer learning from medical datasets can also enhance performance.

2. **Cloud Integration:**To enable large-scale accessibility, deployment on cloud platforms such as AWS, Azure, or Google Cloud is proposed. This would facilitate multi-user access, scalability, and improved computational efficiency.

3. **Database Connectivity:** Integration with structured medical databases or APIs (e.g., WHO datasets) can allow real-time data updates, improving model relevance and adaptability to emerging diseases.

4. **Federated Learning:** Future systems may adopt federated learning to train models collaboratively across distributed devices while preserving user data privacy. This enhances global data diversity without compromising security.

5. **Multilingual Support:** Streamlit's flexibility can be leveraged to extend the system into multiple languages, improving accessibility for non-English-speaking users.

6. **Wearable and IoT Integration:** The methodology can be expanded to support data input from wearable devices, enabling continuous monitoring and real-time health assessments.

7. **Explainable AI (XAI):** Implementing model interpretability tools such as SHAP or LIME can make the diagnostic process more transparent, allowing users to understand symptom contributions to disease predictions.

8. **Blockchain Integration for Medical Integrity:** As an advanced research direction, blockchain can be integrated for immutable logging of diagnostic interactions, ensuring data traceability and trustworthiness.

Through these enhancements, *AI Health Diagnosis* can evolve into a robust, intelligent, and scalable healthcare companion capable of delivering personalized insights while maintaining ethical and technical integrity.

III-L. Summary of Proposed Methodology

The proposed methodology demonstrates a complete end-to-end framework for AI-based medical diagnosis using symptom data. By combining data-driven machine learning with an interactive Streamlit interface, the system bridges accessibility and intelligence in preventive healthcare. The methodology ensures that each subsystem—from data preprocessing and model training to visualization and privacy handling—contributes cohesively toward achieving accurate, interpretable, and responsible AI-driven health predictions.The architecture's modular nature provides scalability and maintainability, while its transparent open-source implementation fosters trust among users and researchers. The primary methodology for mental health analysis involves using **Natural Language Processing (NLP)** to classify text from social media platforms like Twitter and Reddit. The core technique is to fine-tune pre-trained **transformer models** such as BERT and RoBERTa to detect conditions like depression and anxiety. For even greater accuracy, some research proposes creating domain-specific models like **MIRoBERTa** by pre-training on a large corpus of mental health-related text. An alternative methodology uses a novel **Deep Quantum Convolutional Neural Network (QCNN)** to analyze facial expressions as a proxy for a person's mental state, aiming to achieve faster and more accurate results. Foundational work also includes methodologies for creating new, high-quality datasets, such as the **MentalQA** Arabic corpus, which involves scraping medical platforms and using a rigorous annotation schema to label question-and-answer pairs.

For brain tumor analysis, the main proposed methodology is **deep learning-based image segmentation** using multi-modal MRI scans. The central architecture is the **U-Net model**, which is specifically designed for biomedical imaging. A key enhancement proposed is to replace the standard U-Net encoder with a more powerful pre-trained network like **EfficientNet**, which significantly boosts feature extraction and classification accuracy. Another methodology focuses heavily on pre-processing, proposing a two-stage approach where MRI images are first enhanced using **adaptive Wiener filtering and Independent Component Analysis (ICA)** to reduce noise and improve contrast, before a **Support Vector Machine (SVM)** performs the final classification. To address data privacy, **Federated Learning** is also proposed as an architectural methodology, allowing models to be trained collaboratively across different institutions without centralizing sensitive patient data.

Traditional methods for diagnosing these conditions face significant limitations. Issues such as social stigma, a shortage of mental health specialists, unequal access to care, and the potential for misdiagnosis prevent many individuals from receiving timely and effective treatment. In this context, the widespread use of **social media platforms** like Twitter and Reddit is presented as a unique opportunity. These platforms have become vast repositories of user-generated data where people often express their thoughts and feelings more openly than they would in a clinical setting.

The proposed solution across these papers is to harness the power of **Artificial Intelligence (AI)**, **Natural Language Processing (NLP)**, and machine learning to analyze this digital data. Advanced models like **BERT (Bidirectional Encoder Representations from Transformers)** are introduced as powerful tools capable of understanding the complex context of human language, making them ideal for detecting signs of mental distress. In addition to text, facial expressions are identified as another crucial indicator of a person's mental state, leading to the proposal of novel technologies like **Quantum Convolutional Neural Networks (QCNN)** for their analysis. A key motivation is also to address the scarcity of AI resources in non-English languages, which led to the creation of new

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datasets like the Arabic **MentalQA** corpus to build more inclusive tools.

To overcome these limitations, the papers propose automated diagnostic systems built on **deep learning**, particularly **Convolutional Neural Networks (CNNs)**. The **U-Net** architecture is recognized as a highly effective model for medical image segmentation. However, it is also noted that traditional CNNs can struggle to capture comprehensive, long-range features in an image. In response, the research proposes innovative enhancements, such as integrating the powerful **EfficientNet** architecture as the encoder within the U-Net model to improve its feature extraction capabilities and overall accuracy.

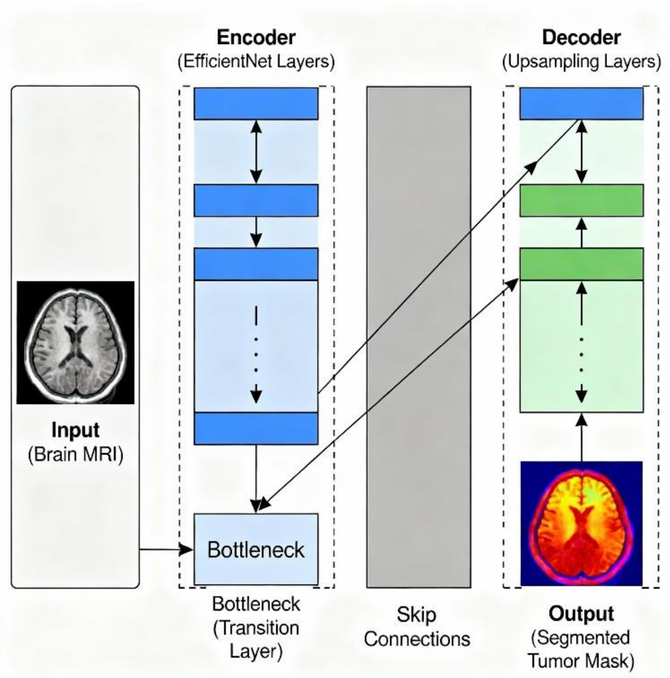
IV. CHALLENGES

Data-Related Challenges: A recurring challenge is the difficulty in obtaining large, high-quality, and well-annotated datasets, which are essential for training robust deep learning models. This is a particular problem in medical imaging, where expert annotation is expensive and time-consuming, and for mental health research in under resourced languages.

Quantum **CNN for Facial Expression Recognition:** The novel Deep Quantum Convolutional Neural Network (QCNN) demonstrated superior performance on several benchmark facial expression datasets. It achieved an accuracy of **81.95%** on KDEF, **73.55%** on SFEW 2.0, and **79.95%** on FER-2013, outperforming other state-of-the-art methods while claiming a significant advantage in computational speed.

Insights from the MentalQA Arabic Corpus: Analysis of the newly created MentalQA dataset revealed high inter-annotator agreement (Fleiss' Kappa of 0.98 for answer strategies), confirming its quality. The most frequent question type from patients was related to **Treatment** (57%), while the most common response strategy from doctors was providing **Information** (75%). Sentiment analysis showed that patient questions were predominantly negative, whereas doctor responses were typically neutral.

Impact of COVID-19: A study on college students in Wuhan during the pandemic found that **37.86%** experienced psychological stress, primarily anxiety. The results also indicated that female students reported higher levels of stress and anxiety (38.88%) compared to male students (28.92%).



Architecture Diagram

Performance of Enhanced U-Net Architectures: Deep learning models based on the U-Net architecture showed exceptional performance. The **EfficientNet-enhanced UNet** model, in particular, achieved a remarkable accuracy of **99.25%** for multiclass brain tumor segmentation on the Figshare dataset (classifying meningioma, glioma, and pituitary tumors). The results highlight the benefit of using powerful pre-trained models as encoders in segmentation frameworks.

V. RESULTS AND DISCUSSIONS

Transformer Model Performance: In text-based mental health detection, pre-trained transformer models like BERT and RoBERTa achieved state-of-the-art results. For instance, in predicting depression from Twitter data, these models reached an accuracy of up to **97%**, significantly outperforming baseline machine learning methods. The effectiveness of domain-specific pre-training was also proven, with the **MIRoBERTa** model achieving a top accuracy and F1-score of **0.847** on a multiclass mental illness classification task using Reddit data.

Effectiveness of Social Media Data: The results validate social media as a rich source for mental health screening. The analysis showed that even small amounts of text, such as a user's bio, can be highly predictive of depression, with models achieving up to **96% accuracy** on this data

Impact of Image Enhancement: A study using a two-module approach demonstrated the critical importance of pre-processing. After applying an initial image enhancement module (using adaptive Wiener filtering, neural networks, and ICA), the classification module achieved an average sensitivity and specificity of **0.991** and a Dice Score (DSC) of **0.981**. This method was also significantly faster than existing

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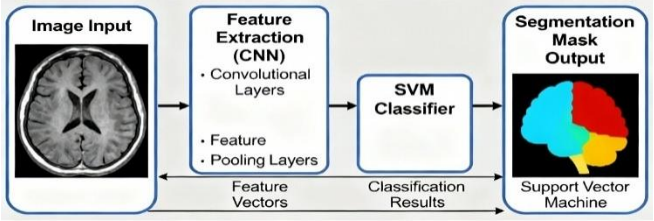
techniques, with an average processing time of just **0.43 seconds**.



Hybrid CNN-SVM Architecture for Brain Tumor Segmentation

Success on Benchmark Datasets (BraTS): On the highly competitive BraTS benchmark, various deep learning methods like cascaded U-Nets and ensemble models consistently delivered high performance. For example, one cascaded model achieved Dice scores of **0.90** for the Whole Tumor, **0.86** for the Tumor Core, and **0.80** for the Enhancing Tumor on the BraTS 2019 validation set.

Viability of Federated Learning: The research confirms that **federated learning** is a viable and effective approach for training models on decentralized medical data. It can achieve performance comparable to models trained on centralized data, all while preserving patient privacy and facilitating multi-institutional collaboration.

Deep Learning vs. Traditional Methods: Across the board, the results show that deep learning models consistently and significantly outperform traditional machine learning and image processing techniques for brain tumor analysis in terms of accuracy, Dice score, and other key metrics.

Data Imbalance: Datasets are often imbalanced, where one class heavily outweighs another (e.g., healthy tissue vs. tumor tissue). This can bias the model, causing it to perform poorly on the minority class, which is often the one of greatest clinical interest.

Variability and Lack of Standardization: Medical data, such as MRI scans, can vary significantly depending on the scanner and clinical protocols, making it difficult for models to generalize across different institutions. Similarly, social media text is notoriously "noisy," filled with slang, sarcasm, and typos that complicate analysis

Privacy and Ethical Concerns: The use of sensitive patient data and personal social media content raises major ethical and privacy issues. While techniques like **federated learning** are proposed as a solution, they come with their own complexities.

Computational Cost and Scalability: Modern deep learning architectures, such as large transformer models and 3D CNNs, are computationally intensive, requiring significant GPU resources and time to train.

Capturing Complex Features: Traditional CNNs have limitations in capturing long-range dependencies, which is important for understanding the full context of a brain tumor. For mental health, accurately interpreting the subtle and often ambiguous language used to express distress remains a persistent challenge. The indistinct or "hazy" borders and varied shapes of brain tumors also make precise segmentation a difficult technical problem.

VI. FUTURE WORK

Data Scarcity and Quality: A recurring challenge is the difficulty in obtaining large, high-quality, and accurately annotated datasets, which are essential for training robust deep learning models. This is particularly pronounced in medical imaging, where expert annotation is expensive and time-consuming, and in mental health research for under-represented languages.Another significant improvement involves enhancing the AI validation pipeline. While current generative AI and peer- review mechanisms ensure contextual evaluation of skills, future versions will incorporate multimodal AI models capable of analyzing text, code repositories, video demonstrations, and project documentation simultaneously.

Data Imbalance: Datasets are often imbalanced, where one class heavily outweighs another (e.g., healthy tissue vs. tumor tissue, or non-depressed vs. depressed posts). This can bias the model, causing it to perform poorly on the minority class, which is often the class of greatest interest

Variability and Lack of Standardization: Medical data, such as MRI scans, can vary significantly depending on the scanner, acquisition protocols, and hospital, making it difficult for models to generalize across different institutions. Similarly, social media text is notoriously "noisy," filled with slang, sarcasm, and typos that complicate analysis. Another paper notes the difficulty in creating a uniform validation process for varied skill proofs like code, videos, and certificates.

Privacy and Ethical Concerns: The use of sensitive patient data and personal social media content raises major ethical and privacy issues.While techniques like **federated learning** are proposed as a solution, they introducetheirownset of complexities.

Computational Cost and Scalability: Modern deep learning architectures, such as large transformer models and 3D CNNs, are computationally intensive. They require substantial GPU memory and can take a long time to train, which can be a bottleneck in resource-constrained environments. Similarly, blockchain-based systems face challenges with transaction costs ("gas fees") and scalability

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as the number of users grows..

Capturing Complex and Nuanced Features: Traditional CNNs have limitations in capturing long-range dependencies within an image, which is important for understanding the full context of a brain tumor. For mental health, accurately interpreting the subtle and often ambiguous language used to express distress is a persistent challenge, even for advanced transformer models. The indistinct or "hazy" borders of brain tumors also make precise segmentation a difficult technical problem.

Overfitting and Generalization: With limited or imbalanced data, complex models are prone to "overfitting," where they memorize the training data but fail to perform well on new, unseen examples. Techniques like data augmentation (artificially creating more training data) are commonly used to mitigate this but require careful implementation.

VII. CONCLUSION

This collection of research underscores the transformative potential of artificial intelligence in addressing complex healthcare challenges, particularly in mental health screening and neuro-oncological diagnostics. The findings consistently demonstrate that advanced computational models can deliver faster, more accurate, and more accessible solutions than traditional methods

In the realm of mental health, the studies show that analyzing digital footprints—such as social media posts on platforms like Reddit and Twitter, or even facial expressions—is a highly effective method for early detection of conditions like depression, anxiety, and suicidal ideation. Transformer-based models, especially those pre-trained on domain-specific language like **MIRoBERTa**, have set a new standard for accuracy in classifying mental illnesses from text. This capability allows for scalable, non-intrusive screening that can empower timely interventions , a need starkly highlighted by the increased psychological stress observed during the COVID-19 pandemic.

In the field of brain tumor analysis, the research confirms that deeplearning architectures, particularly variants of U-Net enhanced with powerful encoders like EfficientNet, are exceptionally effective for the automated segmentation of tumors from multi-modal MRI scans. These models achieve outstanding accuracy (up to 99.25%) in delineating complex tumor sub-regions, which is critical for diagnosis and treatment planning. The importance of pre-processing is also highlighted, with specialized image enhancement techniques shown to significantly improve classification performance. To address the critical issue of data privacy in medical research, federated learning is presented as a viable solution, enabling multi-institutional collaboration without centralizing sensitive patient data.

Ultimately, these studies collectively point toward a future where AI acts as a vital tool for clinicians. By leveraging AI to analyze diverse data sources, from social media text to complex medical images, it is possible to create more robust, efficient, and equitable healthcare systems. Future efforts will likely focus on enhancing the interpretability of these models, ensuring their reliability across diverse populations, and integrating them seamlessly into clinical workflows to improve patient outcomes worldwide.

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