INTEGRATION OF MULTIMODAL NON-INVASIVE SIGNALS FOR EARLY DETECTION OF COGNITIVE IMPAIRMENT

A PROJECT REPORT
(PHASE I)

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BONAFIDE CERTIFICATE

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

ABSTRACT

Early detection of cognitive impairment is vital for preventing and managing neurodegenerative disorders such as Alzheimer's disease and dementia. Traditional assessment methods mainly rely on single-modal approaches like questionnaires or interviews, which may not provide complete or objective insights into an individual's cognitive state. To overcome these limitations, this project proposes a multimodal non-invasive system that integrates facial recognition and questionnaire-based evaluation for improved early detection of cognitive impairment. The system combines facial expressions captured during interaction with questionnaire responses assessing cognitive and emotional parameters. A Convolutional Neural Network (CNN) is used to extract facial features and classify emotional states that may indicate cognitive decline, while the Naïve Bayes classifier analyzes questionnaire responses to compute a probability score for cognitive issues. The mean of both scores produces a final cognitive assessment score out of 10, enhancing prediction reliability by merging visual and behavioral data. This non-invasive multimodal approach improves accuracy and robustness compared to single-modal systems and offers a practical method for regular monitoring. The project demonstrates the potential of AI-based multimodal frameworks in enabling precise and early diagnosis of cognitive impairments, promoting timely intervention and better quality of life for at-risk individuals.

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LIST OF ABBREVATIONS

ABBREVATION	EXPANSION
CNN	Convolutional Neural Network
ML	Machine Learning
MCI	Mild Cognitive Impairment
DL	Deep Learning
LSTM	Long Short-Term Memory
RNN	Recurrent Neural Network
TPR	True Positive Rate
NPR	False Positive Rate
UI	User Interface
API	Application Programming Interface
AL	Alzhemier's Disease
ROC	Receiver Operating Characteristic

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

The global rise in cognitive disorders, including dementia and Alzheimer's disease, has become a growing concern as the elderly population continues to increase worldwide. Cognitive impairment affects essential mental functions such as memory, reasoning, and attention, gradually reducing an individual's independence and quality of life. With the number of affected individuals projected to grow significantly in the coming years, there is an urgent need for effective and accessible methods to identify early signs of cognitive decline before they progress to severe stages.

Conventional cognitive assessment techniques largely rely on single-modal approaches such as clinical interviews or questionnaire-based tests. Although these methods provide useful insights, they are often subjective, time-consuming, and dependent on expert supervision. Many individuals go undiagnosed due to the absence of regular monitoring and the difficulty of accessing specialized healthcare facilities. Hence, there is a strong demand for a non-invasive, reliable, and continuous evaluation system that can assist in the early detection of cognitive changes.

To address these challenges, this project proposes a multimodal non-invasive system that combines facial recognition and questionnaire-based evaluation for early detection of cognitive impairment. Facial expressions can reflect subtle emotional and behavioral cues associated with cognitive decline, while structured questionnaires capture self-reported cognitive, behavioral, and emotional states. For image-based facial analysis, a Convolutional Neural Network (CNN) is used to classify expressions, whereas the Naïve Bayes algorithm evaluates questionnaire responses to estimate the likelihood of cognitive impairment. The final cognitive assessment score is derived by averaging the outcomes from both modalities, providing a more comprehensive evaluation compared to single-modal systems.

1.2 PROBLEM STATEMENT

The Cognitive impairment is a progressive condition that affects memory, thinking, and behavior, often leading to disorders such as dementia and Alzheimer's disease. With the rapid growth of the elderly population worldwide, early and reliable detection of cognitive impairment has become a critical healthcare priority. However, most existing detection methods are single-modal, relying exclusively on either clinical questionnaires or physical examinations. These approaches often lack objectivity, require expert supervision, and are not suitable for large-scale or continuous monitoring. Consequently, many individuals with early cognitive decline remain undiagnosed until the condition reaches an advanced stage.

A major limitation of the existing systems lies in their dependence on subjective responses or isolated physiological parameters, which do not fully capture the emotional and behavioral changes associated with cognitive decline. Emotional expression, in particular, is a crucial but underutilized indicator of mental and cognitive health. Subtle facial expressions such as sadness, confusion, or reduced responsiveness can provide valuable cues for early detection, yet traditional single-modal systems fail to analyze such non-verbal features effectively.

To address these limitations, this project introduces a multimodal non-invasive approach that integrates facial emotion recognition and questionnaire-based evaluation to enhance early detection accuracy. The proposed system uses a Convolutional Neural Network (CNN) trained on facial images categorized into emotional states such as *happy* and *sad*. Simultaneously, a Naïve Bayes classifier processes questionnaire responses related to memory, attention, and daily behavioral patterns, generating a probability score indicating the likelihood of cognitive impairment.

The outputs from both modalities are then combined by calculating the mean of the CNN classification score and the Naïve Bayes probability score, resulting in a final cognitive assessment score out of 10. This fusion technique ensures that both emotional and behavioral aspects are considered, making the evaluation more comprehensive and objective.

1.3 AIM AND SCOPE

The main aim of this project is to design and develop a multimodal non-invasive system for the early detection of cognitive impairment by integrating facial emotion recognition and questionnaire-based evaluation. The system seeks to provide a more comprehensive and objective assessment of cognitive health by analyzing both visual emotional cues and self-reported behavioral data. By combining these two modalities, the project aims to identify subtle cognitive changes at an early stage, which can help in timely medical intervention and effective management of cognitive disorders.

The scope of this project extends to building a reliable framework capable of assessing emotional and cognitive parameters without requiring invasive procedures or continuous clinical supervision. The Convolutional Neural Network (CNN) model is trained to recognize facial emotions such as *happy* and *sad*, which often serve as indicators of cognitive and emotional well-being. Meanwhile, the Naïve Bayes algorithm evaluates questionnaire responses related to memory, focus, and reasoning ability, producing a probability score of potential cognitive decline. The combination of these two independent results provides a final cognitive assessment score out of 10, representing the overall cognitive state of an individual.

This project's scope also includes demonstrating that multimodal evaluation improves accuracy and reliability compared to traditional single-modal systems. It emphasizes the advantages of non-invasive, low-cost, and user-friendly assessment methods that can be applied for regular monitoring of at-risk individuals, particularly the elderly and the people who having difficulty in remembering things . In the long term, this system can be extended for use in healthcare centers, screening programs, or even home-based cognitive monitoring platformshus, the project not only contributes to technological innovation in health monitoring but also supports early diagnosis, preventive healthcare, and better quality of life for individuals showing early signs of cognitive decline. Furthermore, it provides a scalable framework that can be customized for different age groups and risk levels.

1.4 RESEARCH CONTRIBUTION

The This project makes a significant contribution to the field of cognitive health assessment by introducing a multimodal non-invasive framework for the early detection of cognitive impairment. Unlike traditional systems that rely solely on single-modal inputs such as questionnaires or clinical interviews, this study integrates facial emotion recognition and questionnaire-based evaluation to achieve a more comprehensive and reliable assessment. This multimodal approach enhances diagnostic accuracy by combining both visual and behavioral cues, which together provide a deeper understanding of cognitive and emotional states.

A key contribution of this research lies in the development and training of a CNN model capable of classifying facial emotions such as *happy* and *sad*, which are often early indicators of cognitive and emotional decline. The trained model effectively captures subtle facial variations and expression patterns that may not be easily detected by the human eye. Alongside this, the use of the Naïve Bayes algorithm for questionnaire analysis introduces a probabilistic approach to evaluating cognitive responses, generating a quantitative score that reflects the likelihood of cognitive impairment.

Another important contribution of this work is the integration of the CNN and Naïve Bayes outcomes to compute a final cognitive assessment score out of 10, which represents the overall cognitive state of the individual. This fusion technique provides a balanced, data-driven evaluation that is both objective and non-invasive. The system design emphasizes simplicity, accessibility, and cost-effectiveness, making it suitable for deployment in healthcare centers, elderly care homes, and even remote screening setups.

Overall, the research contributes to advancing multimodal cognitive
monitoring systems by demonstrating that the combination of facial emotion recognition and questionnaire analysis can significantly improve early detection rates.

1.5 SIGNIFICANCE OF THE STUDY

The number of people with memory and thinking problems, such as dementia and Alzheimer's disease, is increasing quickly as the world's elderly population grows. Cognitive impairment affects important mental abilities like memory, understanding, and attention, which gradually reduce a person's independence and quality of life. As the number of people affected continues to rise, it is essential to find simple and effective ways to detect the early signs of cognitive problems.

Early detection plays a vital role in helping doctors and families provide timely care, which can slow down the progression of the disease and improve the patient's overall well-being. However, many individuals remain undiagnosed in the early stages because the symptoms are often mild, intermittent, or mistaken for normal aging. Regular screening and continuous observation are therefore crucial for recognizing early cognitive changes that might otherwise go unnoticed.

Developing easy, non-invasive, and reliable systems for early detection can lead to significant improvements in healthcare outcomes. Such systems can assist medical professionals in making more accurate diagnoses and enable families to make informed decisions about care and support. Moreover, these systems can reduce the emotional and financial strain on healthcare institutions and caregivers by allowing interventions to begin at an earlier, more manageable stage of the disease.

The integration of artificial intelligence (AI) and multimodal data analysis in cognitive health evaluation offers a new dimension of accuracy and efficiency. By analyzing diverse data sources—such as voice, facial expression, movement patterns, and medical imaging—AI-based systems can identify subtle cognitive changes that traditional assessments may overlook. This not only enhances diagnostic precision but also provides opportunities for personalized monitoring and treatment planning.

CHAPTER 2

LITERATURE SURVEY

2.1 ANAYSIS OF MULTIMODEL METHODS FOR COGNITIVE HEALTH EVALUATION

The evaluation of cognitive health has evolved significantly with advancements in multimodal technologies. Traditional diagnostic approaches often relied on single-modality data such as neuropsychological tests or brain imaging. However, these methods alone are often insufficient to capture the complex nature of cognitive decline. Recent studies emphasize the integration of multiple data modalities—including neuroimaging, speech, facial expression, physiological signals, and behavioral patterns—to improve diagnostic accuracy and early detection of cognitive impairment.

Multimodal analysis leverages the complementary strengths of diverse data sources. For instance, combining functional MRI (fMRI) with electroencephalogram (EEG) data enables both spatial and temporal understanding of brain activity. Similarly, speech and facial cues have been explored as non-invasive biomarkers for detecting subtle cognitive changes. Machine learning and deep learning models are often employed to extract, fuse, and interpret information from these heterogeneous data streams, providing robust insights into an individual's cognitive state.

Recent research highlights that multimodal fusion strategies can be categorized as early fusion, late fusion, and hybrid fusion. Early fusion integrates raw data or features before model training, while late fusion combines independent model outputs. Hybrid fusion techniques seek to balance interpretability and performance by integrating both feature-level and decision-level information. These approaches have demonstrated improved performance in detecting disorders such as Alzheimer's disease, mild cognitive impairment (MCI), and dementia when compared to unimodal methods.

2.2 SURVEY OF MULTIMODAL FOR COGNITIVE IMPAIRMENT

Multimodal approaches for the early detection of cognitive impairment leverage a combination of behavioral, physiological, and neuropsychological signals to provide a comprehensive assessment of cognitive health. Unlike traditional single-task evaluations, which often rely on subjective tests or isolated measurements, multimodal systems integrate data from facial expressions, eye-tracking, gait analysis, and other non-invasive biomarkers to capture subtle changes associa Multimodal approaches for the early detection of cognitive impairment leverage a combination of behavioral, physiological, and neuropsychological signals to provide a comprehensive assessment of cognitive health. Unlike traditional single-task evaluations, which often rely on subjective tests or isolated measurements, multimodal systems integrate data from speech patterns, handwriting dynamics, facial expressions, eye-tracking, gait analysis, and other non- invasive biomarkers to capture subtle changes associated with conditions such as Mild Cognitive Impairment (MCI) and Alzheimer's Disease (AD).

Recent studies demonstrate that combining multiple modalities improves sensitivity and specificity, as cross-modal correlations can reveal cognitive deficits that may be missed when modalities are analyzed in isolation. Machine learning and deep learning techniques are commonly employed to extract meaningful features, handle high-dimensional data, and classify impairment levels accurately. Furthermore, multimodal approaches facilitate longitudinal monitoring, enabling early detection of cognitive decline before clinical symptoms become pronounced. Despite the demonstrated benefits, challenges remain in standardizing datasets, managing missing or noisy data, and ensuring model generalizability across diverse populations.

2.3 SAFETY, RELIABILITY AND TRUSTWORTHINESS IN MULTIMODAL COGNITIVE ASSESSMENT SYSTEMS

Ensuring the safety, reliability, and trustworthiness of multimodal cognitive assessment systems is critical, particularly when these tools are applied in clinical and home-based settings. Such systems must perform robustly across diverse populations, accounting for variations in age, language, culture, and education, as well as environmental factors that may introduce noise into the collected data. Ethical considerations, including patient privacy, informed consent, data security, and mitigation of biases, are central to responsible deployment. Additionally, the interpretability of machine learning models is essential for clinical acceptance, as healthcare professionals must understand the basis of predictions to trust and act upon them. Efforts to enhance model transparency, combined with rigorous validation across heterogeneous populations, help establish these systems as reliable and safe tools for early cognitive impairment

2.4 ENHANCING DETECTION ACCURACY VIA MULTIMODAL DATA FUSION

Detection accuracy in multimodal cognitive impairment systems can be significantly improved through effective data fusion techniques, which combine information from multiple behavioral and physiological sources. Early fusion involves integrating raw or preprocessed features from different modalities before classification, whereas late fusion combines predictions from separate modality-specific models. Hybrid fusion methods leverage both strategies to optimize performance. Machine learning and deep learning algorithms play a key role in extracting meaningful features, learning complex inter-modal relationships, and addressing challenges such as missing or noisy data. By integrating multiple complementary signals, multimodal fusion provides a more holistic representation of cognitive function, resulting in higher sensitivity and specificity compared to single-modality approach.

2.5 NON-INVASIVE SENSING TECHNOLOGIES FOR COGNITIVE HEALTH MONITORING

The non-invasive sensing technologies form the backbone of modern cognitive monitoring systems, enabling continuous, unobtrusive data collection. Wearable sensors, mobile devices, and IoT-enabled platforms capture speech, handwriting dynamics, facial expressions, motor activity, and physiological signals without causing discomfort or risk to the patient.These technologies support long-term monitoring of cognitive health in natural environments, providing a more accurate understanding of daily behavioral and neurological changes.

Remote assessment tools and telemedicine applications further expand access to cognitive monitoring, particularly for individuals in rural or underserved areas who may not have access to specialized healthcare facilities.

Modern non-invasive systems rely heavily on sensors such as accelerometers, gyroscopes, and photoplethysmography (PPG) for tracking motion, heart rate variability, and other physiological parameters associated with cognitive functioning. Speech analysis tools can detect subtle changes in language fluency, tone, and rhythm—early indicators of cognitive decline—while facial recognition systems assess emotional expression and responsiveness. Eye-tracking devices and digital handwriting analysis also provide valuable insights into attention span, motor control, and memory retention. These multimodal sensing methods offer rich datasets that can be analyzed using artificial intelligence algorithms to identify patterns and predict cognitive deterioration.

One of the most promising aspects of non-invasive sensing is its ability to provide real-time, continuous, and remote cognitive assessment. Unlike traditional clinical evaluations, which are episodic and time-limited, these systems allow for ongoing monitoring that captures natural fluctuations in cognitive performance. This continuous data stream supports early intervention strategies, helping healthcare providers and caregivers respond promptly to any signs of decline.

2.6 COMPARATIVE ANALYSIS

The comparative analysis helps to evaluate how the proposed system differs from existing methods and what improvements it offers. In most previous studies, single-modal systems were used for detecting cognitive impairment—either based on questionnaire responses or facial expression analysis alone. While these approaches provided useful insights, they often lacked accuracy and reliability because they focused on only one aspect of cognitive behavior.

Traditional questionnaire-based systems rely on manual input and human observation, which can lead to subjective results and inconsistent assessments. Similarly, systems based only on facial recognition can misinterpret emotions due to lighting, pose variations, or environmental conditions, reducing the precision of detection. These limitations highlight the need for a more comprehensive and integrated approach.

The proposed project addresses these challenges by introducing a multimodal framework that combines both facial recognition and questionnaire-based evaluation. The Convolutional Neural Network (CNN) model analyzes facial images to detect emotions such as *happy* and *sad*, which may indicate underlying cognitive states. At the same time, the Naïve Bayes algorithm processes questionnaire data to calculate a probability score of cognitive decline. By taking the mean of both results, the system produces a more balanced and accurate cognitive assessment score out of 10.

Compared to existing single-modal systems, the proposed multimodal system provides higher reliability, improved detection accuracy, and a more holistic assessment. It also ensures non-invasiveness, user comfort, and continuous monitoring capability, making it suitable for early diagnosis and regular cognitive health evaluation. Thus, the comparative analysis clearly shows that integrating multiple modalities significantly enhances the performance and effectiveness of cognitive impairment detection systems.

2.7 MOTIVATION AND SUMMARY

Cognitive impairment has become a major global concern, especially with the increasing elderly population and the growing number of people affected by dementia and Alzheimer's disease. Early signs such as memory loss, confusion, or emotional imbalance often go unnoticed until the condition becomes severe. Traditional screening methods like medical checkups or clinical questionnaires are time-consuming, costly, and not suitable for frequent monitoring. This situation motivated the need for a non-invasive, reliable, and accessible system that can detect early cognitive decline effectively.

The project is driven by the idea of overcoming the limitations of single-modal approaches, which depend only on one type of input data. A single test, such as a questionnaire or facial analysis alone, may not give a complete picture of a person's cognitive state. To address this, the proposed system combines facial emotion recognition and questionnaire-based evaluation to form a multimodal system that provides more accurate and meaningful results. The Convolutional Neural Network (CNN) model is trained to detect emotions such as *happy* and *sad*, which are often linked to cognitive and emotional health. Simultaneously, the Naïve Bayes classifier processes questionnaire responses to calculate a probability score that reflects possible cognitive issues.

By integrating the outputs of both modalities, the system computes a final cognitive assessment score out of 10, giving a balanced and precise indication of cognitive well-being. This approach ensures a comprehensive evaluation by merging objective visual data with subjective user responses. The system's non-invasive nature allows comfortable and regular use, making it suitable for early diagnosis and continuous monitoring.

In summary, this project introduces an innovative and user-friendly framework that contributes to the advancement of cognitive health monitoring. It emphasizes the importance of combining multiple data sources for better prediction accuracy and timely intervention.

CHAPTER 3

SYSTEM ANALYSIS OF MULTIMODAL COGNITIVE ASSESSMENT

3.1 SYSTEM ANALYSIS

The System analysis serves as a crucial phase in the development of the proposed multimodal cognitive assessment system. It involves understanding the existing challenges, defining system requirements, and analyzing the functionalities needed to achieve the project objectives effectively. The main goal of this phase is to thoroughly study how different components—such as facial recognition and questionnaire-based evaluation—can be integrated into a unified, reliable, and efficient framework for early detection of cognitive impairment.

In the context of this project, system analysis focuses on identifying the shortcomings of existing single-modal systems and determining how a multimodal approach can overcome those limitations. Traditional methods, which rely solely on clinical tests or behavioral assessments, often lack consistency and depth in evaluating cognitive health. By analyzing both facial emotion patterns using Convolutional Neural Networks (CNN) and questionnaire responses through Naïve Bayes classification, the system aims to enhance prediction accuracy and ensure a more comprehensive evaluation of cognitive functions.

The system analysis also involves studying the data flow, input and output processes, and the interaction between modules to ensure smooth functionality. This includes capturing facial data, processing emotional features, analyzing questionnaire responses, and integrating both results to generate a final cognitive score out of 10. Through this analytical approach, the project ensures that the proposed system is not

3.2 EXISTING SYSTEM

The existing cognitive assessment systems primarily rely on single-modal evaluation techniques, such as traditional neuropsychological tests, facial recognition, speech analysis, or questionnaire-based assessments. These methods focus on analyzing only one type of data at a time, which often limits the accuracy and reliability of the results. For example, questionnaire-based evaluations depend heavily on the participant's honesty, memory, and understanding, which can lead to subjective or inconsistent outcomes. Similarly, facial or speech-based assessments alone may be affected by external factors like lighting conditions, background noise, or emotional variations, making the analysis less precise.

Traditional systems also face challenges in detecting early signs of cognitive impairment such as mild memory loss or subtle behavioral changes. Because they analyze limited data, these systems may fail to identify early symptoms of cognitive decline, leading to delayed diagnosis and treatment. Furthermore, they are often time-consuming, invasive, and difficult to use for continuous monitoring, as they require in-person testing and expert supervision. This makes them impractical for large-scale or frequent screening, especially among elderly individuals who may face mobility or accessibility issues.

Another major limitation of the existing systems is their inability to integrate multiple behavioral and physiological cues for a comprehensive understanding of the patient's cognitive state. Without multimodal data, it becomes difficult to assess emotional, behavioral, and cognitive aspects simultaneously. As a result, clinicians often rely on fragmented information, which may not reflect the complete cognitive profile of the individual. This lack of integration reduces diagnostic accuracy and makes it challenging to track subtle cognitive changes over time.

Moreover, many of the current systems are not designed for real-time or remote assessment. They typically require patients to visit hospitals or specialized centers, limiting continuous observation in everyday environments.

3.3 PROPOSED SYSTEM

In contrast, The proposed multimodal cognitive impairment risk assessment system addresses the limitations of existing systems that rely on a single approach by integrating multiple input modalities, including speech analysis, text analysis, handwriting patterns, and facial expressions, to ensure greater accuracy and reliability. Each modality is processed using suitable machine learning techniques, such as natural language processing for speech and text, pattern recognition for handwriting, and CNN-based models for facial expression analysis. These diverse inputs are then combined through multimodal data fusion to generate a comprehensive cognitive health profile. The results are delivered in the form of a cognitive impairment risk assessment report, accessible through a user-friendly web interface where users can upload data and receive actionable outcomes seamlessly. By leveraging multiple approaches instead of depending on a single method, the proposed system significantly enhances robustness, reduces bias, and provides a more trustworthy solution for early detection and timely intervention in healthcare.

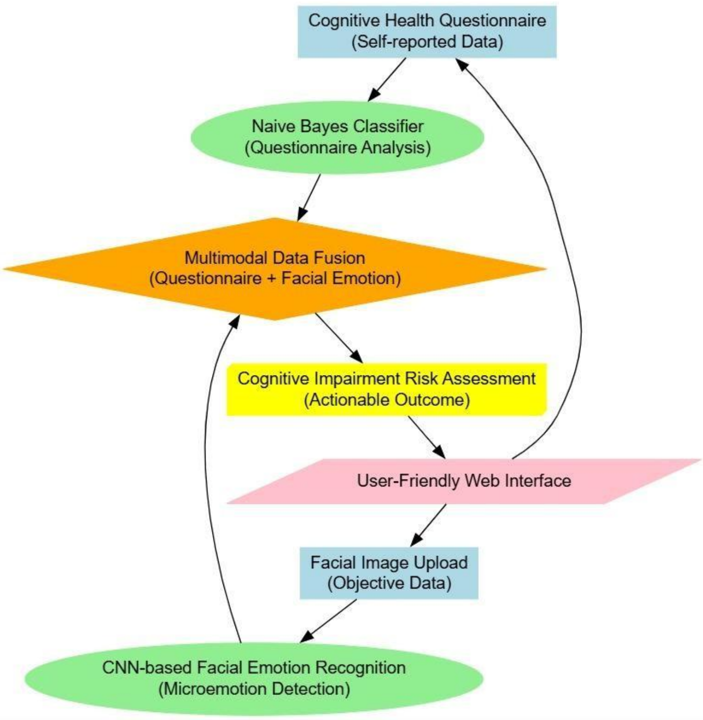

FIG 3.3 PROPOSED SYSTEM

CHAPTER 4

SYSTEM ARCHITECTURE

4.1 SYSTEM OVERVIEW

The proposed system is designed around a Convolutional Neural Network (CNN) architecture that efficiently extracts discriminative visual features from various image-based modalities, such as facial frames and handwriting samples. It follows a modular pipeline structure that can be easily extended to include additional modalities like speech, eye-tracking, and handwriting, enabling a comprehensive multimodal cognitive assessment framework.

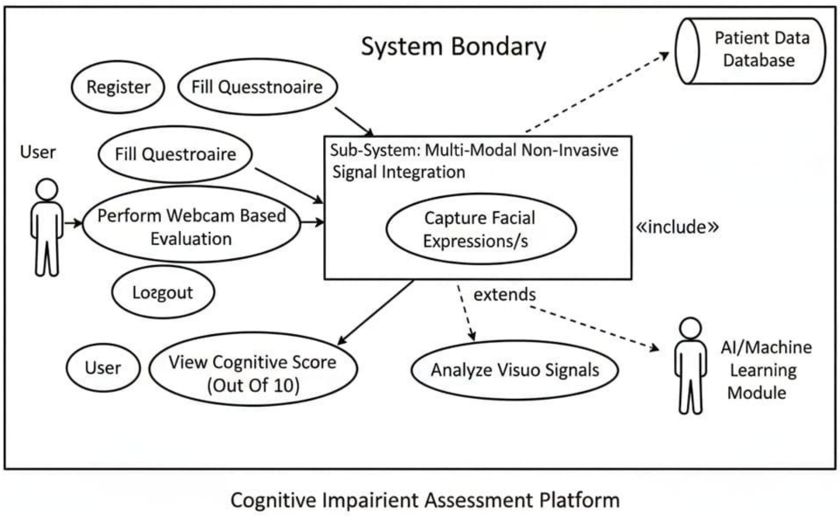

FIG 4.1 SYSTEM USECASE

The CNN architecture is structured to progressively capture hierarchical visual representations. The first convolutional layer (Conv1) employs 32 filters of size 3×3 with a stride of 1 and ReLU activation to detect basic edges and textures. The second layer (Conv2) uses 64 filters to learn intermediate patterns such as combinations of edges and simple facial or handwriting structures. The third layer (Conv3) applies 128 filters to capture more complex, high-level features associated with expressions, gestures, or other fine-grained cognitive cues. Following the convolutional blocks, MaxPooling layers with a 2×2 window are applied to reduce spatial dimensions, control overfitting, and retain the most salient features.

After feature extraction, the network transitions to the classification stage through fully connected (FC) layers. The first fully connected layer (FC1) consists of 128 neurons, and the second (FC2) includes 64 neurons, both activated using ReLU functions to introduce nonlinearity and improve the network's decision-making capability. The final output layer utilizes either a Softmax activation for multi-class classification or a Sigmoid activation for binary classification, generating probabilistic outputs corresponding to the detected cognitive or emotional state.

To enhance regularization and training stability, the architecture incorporates several optimization techniques. Dropout layers with rates between 0.3 and 0.5 are applied after the fully connected layers to prevent overfitting by randomly disabling a fraction of neurons during training. Batch normalization is performed after convolutional layers to stabilize training dynamics and enable the use of higher learning rates. Additionally, weight decay (L2 regularization) is integrated into the optimizer to further reduce overfitting and improve generalization performance.

This CNN structure was specifically chosen due to its balance between efficiency and performance. The use of small 3×3 filters ensures effective learning of local spatial features while keeping computational costs low. The moderate depth of the model, combined with the compact 50×50 input size, allows for faster training and seamless deployment on low-power or edge devices, making the system practical for real-world applications.

Moreover, the system's modular design enables multimodal integration, where CNN-derived embeddings from visual inputs (such as the output of FC2) can be concatenated with features from other data sources like handwriting dynamics, speech features, or questionnaire-based assessments. These combined feature vectors are then processed through a fusion and classification block, facilitating early or hybrid fusion approaches without retraining the individual modality encoders. This multimodal capability enhances the system's robustness and provides a more holistic understanding of cognitive health.

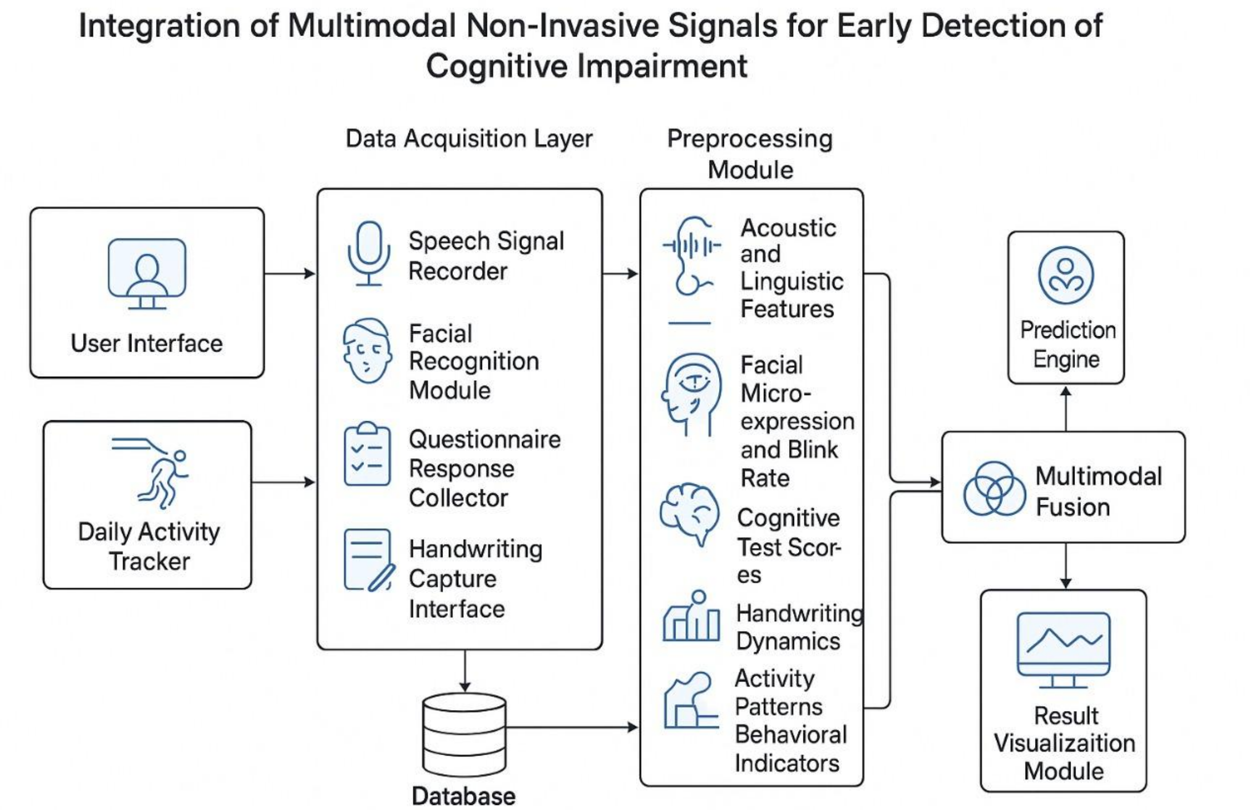

FIG 4.2 SYSTEM ARCHITECTURE

4.2 DATA COLLECTION AND PREPROCESSING

The proposed system utilizes a diverse range of data sources to capture multiple dimensions of cognitive and emotional behavior. The primary modalities include facial expressions, handwriting samples, speech recordings, and questionnaire responses, with optional extensions such as eye-tracking metrics, accelerometer data, and physiological sensor readings. Facial data are collected as either still images or video frames during cognitive or emotional assessment tasks, where the subject's expressions provide crucial insights into mood and cognitive function.

Handwriting samples are gathered through scanned or photographed drawings and written texts, such as clock drawing tests or written responses. Speech data are obtained from short audio recordings of verbal interactions or reading tasks, enabling the extraction of acoustic and linguistic features that reflect cognitive states. Questionnaire responses are collected in structured formats, containing categorical or ordinal answers that can be quantified for analysis. Additional modalities like eye-tracking and accelerometer data can further enhance the system's accuracy by providing information about gaze patterns, movement stability, or physical activity levels.

To ensure reliable and consistent data collection, specific best practices are followed. For facial and video data, uniform lighting conditions, consistent camera distances, and neutral backgrounds are maintained to minimize environmental noise. Metadata such as device resolution, frame rate, and microphone sampling rate are recorded to aid in preprocessing and reproducibility. Ethical considerations are prioritized, ensuring that all participants provide informed consent and that personal identifiers are anonymized or pseudonymized to maintain privacy and confidentiality.

The preprocessing phase is critical for preparing multimodal data for model training. When multiple modalities are captured simultaneously—such as audio and video—synchronization and alignment are performed to ensure that features correspond to the same temporal window. Visual data undergo resizing and cropping, where face detection algorithms (such as OpenCV's Haar cascades or MTCNN) are used to locate the face region, which is then cropped and resized to 50×50 pixels.

Longer recordings are segmented into fixed-length windows, typically between one and three seconds, to provide consistent input sizes for time-sensitive models such as CNN-LSTM architectures.

To improve model robustness and reduce overfitting, various data augmentation techniques are employed. Image-based augmentations include rotations, flips, and brightness adjustments, while audio augmentations involve time-stretching and the addition of background noise to simulate real-world variability. Synthetic data generation is also used to balance datasets and increase diversity. Feature extraction is then performed for non-image modalities: speech features such as **Mel-Frequency Cepstral Coefficients** (MFCCs), chroma, spectral contrast, and zero-crossing rate are computed for each window and aggregated statistically; handwriting dynamics are analyzed in terms of stroke velocity, pressure, and curvature, or extracted as image-based features if only static images are available; questionnaire data are encoded using one-hot or ordinal encoding, and composite metrics such as memory or attention scores may be derived for enhanced interpretability.

Finally, rigorous quality control ensures the integrity of the dataset. Corrupted, incomplete, or outlier samples are removed before training. To prevent model bias, class imbalances—such as unequal distributions of “happy” and “sad” samples—are addressed through oversampling, data augmentation, or class-weighted loss functions. The dataset is also partitioned carefully into training, validation, and test sets, ensuring that subjects in the test set are not included in the training phase. This separation helps assess the model’s generalization capability and ensures reliable performance across diverse individuals and environments.

4.3 FEATURE EXTRACTION USING CONVOLUTIONAL NEURAL NETWORKS

The proposed system leverages Convolutional Neural Networks (CNNs) to process image-based modalities such as facial expressions and handwriting samples, enabling efficient learning of hierarchical spatial features. In the initial layers, the CNN captures low-level visual patterns such as edges, corners, and textures, while deeper layers progressively learn complex and high-level features like facial muscle movements, mouth curvature, eyebrow positions, and other subtle expressions associated with cognitive and emotional states.

The final fully connected (FC) embeddings generated by the CNN serve as dense vector representations that summarize the most relevant spatial information from the input data, which can then be used for classification or integrated into a multimodal fusion model.

The design of the CNN architecture follows well-established deep learning principles optimized for performance and efficiency. Each convolutional layer typically employs a 3×3 kernel with padding = 1 and stride = 1, which maintains the spatial resolution before pooling and ensures fine-grained feature extraction. MaxPooling with a 2×2 filter is applied after certain convolutional layers to progressively reduce the height and width of the feature maps by a factor of two, minimizing computational cost while preserving the most important spatial information. The ReLU activation function is used throughout the convolutional and fully connected layers due to its simplicity and ability to mitigate the vanishing gradient problem, while the final output layer employs Softmax for multi-class classification or Sigmoid for binary classification tasks.

In terms of training configuration, the model can be optimized using either the Adam optimizer (with a learning rate around 1e-3) or SGD with momentum (learning rate around 1e-2 with decay), depending on convergence behavior observed during validation. The loss function is chosen based on the problem type—Categorical Cross-Entropy for multi-class problems or Binary Cross-Entropy for binary classification. The model typically trains with a batch size between 32 and 128, depending on GPU memory availability, and for 30 to 100 epochs with early stopping to prevent overfitting.

For modalities with temporal or sequential characteristics—such as speech or facial video sequences—the architecture is extended to capture both spatial and temporal dependencies. One approach involves converting audio signals into spectrograms and treating them as 2D images, allowing the CNN to extract spatially distributed time-frequency patterns. Alternatively, a hybrid CNN-RNN model can be used, where CNN layers extract frame-level embeddings that are subsequently passed through a Bidirectional LSTM (Bi-LSTM) or Transformer module for temporal modeling.

This setup captures both short-term and long-term dependencies in sequential data, with attention pooling mechanisms further enhancing interpretability by highlighting the most relevant time segments for classification.

To facilitate multimodal feature fusion, the CNN is designed to output a fixed-size embedding vector (typically 64 or 128 dimensions) that can be easily concatenated with embeddings from other modalities such as speech or handwriting. This standardized representation ensures compatibility between different feature spaces and simplifies downstream fusion and classification processes.

Overfitting prevention is a critical aspect of the system's robustness. Several techniques are employed, including data augmentation, dropout regularization, and batch normalization to improve generalization. Additionally, class-weighted loss functions are used when handling imbalanced datasets to prevent bias toward dominant classes. Training and validation performance are continuously monitored using metrics such as loss curves and accuracy plots, with early stopping applied when validation loss no longer improves.

Overall, this CNN-based feature extraction module forms the backbone of the cognitive impairment detection system by providing compact, discriminative, and multimodal-ready representations that enhance both accuracy and scalability.

4.4 MULTIMODAL DATA FUSION

Combining multiple modalities significantly enhances the robustness, accuracy, and sensitivity of the cognitive impairment detection system by integrating complementary information from diverse sources such as facial expressions, speech patterns, and questionnaire responses. Each modality captures unique aspects of cognitive and emotional behavior—visual cues represent facial muscle dynamics, speech captures tone and fluency, while questionnaire responses reflect subjective cognitive assessments. By fusing these modalities, the system can detect subtle cognitive changes that may not be apparent when analyzing a single modality, resulting in a more reliable and comprehensive evaluation of a subject's cognitive state.
There are several fusion strategies commonly used in multimodal learning, each with specific advantages and trade-offs.

This approach enables the model to learn complex cross-modal correlations at the feature level, improving its ability to capture intricate dependencies between modalities.

However, early fusion requires that features be synchronized in time and scaled comparably across modalities, making it sensitive to missing or noisy inputs. For example, in this approach, the combined feature vector $z = [f_{CNN}; f_{speech}; f_{question}]$represents the concatenation of embeddings from CNN, speech, and questionnaire modalities, which is then passed through fully connected layers and a softmax classifier for final prediction.

Late fusion (decision-level fusion), on the other hand, operates at the output stage of individual modality-specific classifiers. Each modality independently produces a probability score or decision output, which are then combined using averaging, weighted averaging, or a meta-classifier to generate the final decision. This method is easier to implement and more robust to missing modalities since each modality can function independently. However, it may lose some feature-level interactions that could enhance interpretability and accuracy. In a typical implementation, the final decision can be computed as a weighted combination of outputs from individual classifiers—for instance,

$$\text{Final Score} = w_1 p_{CNN} + w_2 p_{NB} + \cdots$$

A hybrid fusion approach combines the strengths of both early and late fusion. It learns shared representations where possible (as in early fusion) while maintaining independent decision-level pathways (as in late fusion) for resilience against missing data. Attention-based modules can also be integrated to dynamically assign weights to each modality depending on its reliability and relevance for a given sample, thereby improving adaptability and interpretability. In cases where data from certain modalities are missing or noisy, the system handles them effectively using modality presence masks, which indicate the availability of each modality. Missing modalities are replaced with zero vectors or reduced weights during fusion. Moreover, modality dropout—intentionally omitting random modalities during training—is used to make the model more robust to real-world conditions where incomplete data might occur.

In the context of this project, where the CNN model provides an emotion-based probability score and the Naïve Bayes classifier yields a probability derived from questionnaire data, a late fusion strategy was adopted.

The final cognitive impairment score is calculated as the mean of the two probabilities, ensuring interpretability and simplicity while maintaining robustness. Mathematically, this can be represented as:

$$\text{Final Score} = \left(\frac{p_{CNN} + p_{NB}}{2}\right) \times 10$$

This formula scales the combined output to a 0–10 range, aligning with the system's standardized evaluation metric for cognitive assessment.

Additionally, attention-based fusion could allow the model to dynamically adjust the influence of each modality based on input reliability and contextual cues. These enhancements would make the system even more adaptable, intelligent, and effective for real-world deployment in continuous cognitive health monitoring.

4.5 CLASSIFICATION AND PREDICTION

The classification and prediction phase is the core component of the multimodal cognitive impairment detection system. It integrates the outputs from multiple modalities—specifically facial emotion recognition through Convolutional Neural Networks (CNN) and questionnaire-based evaluation using the Naïve Bayes algorithm—to deliver a unified and interpretable cognitive assessment score. This stage transforms multimodal data into clinically meaningful predictions by combining machine learning outputs, calibrating probability scores, and mapping results to user-friendly scales.

The CNN classifier is responsible for image-based classification, particularly the analysis of facial emotions that may indicate cognitive or emotional anomalies. It processes the preprocessed facial images to produce class probabilities (for example, *happy*, *sad*, or *neutral*). The CNN's hierarchical feature extraction layers identify fine-grained emotional cues such as micro-expressions, gaze direction, and muscle movement patterns.

The advantage of Naïve Bayes lies in its simplicity, interpretability, and computational efficiency. Despite its basic probabilistic assumptions, it often performs well in structured questionnaire assessments, providing a clear probabilistic interpretation of each response pattern.

Optionally, a meta-classifier or ensemble model (such as logistic regression or a small multi-layer perceptron) can be implemented to combine the outputs of the CNN and Naïve Bayes classifiers more optimally. This ensemble approach learns the best weighting for each modality's contribution, thus improving overall accuracy and robustness. However, in this project, a simpler late fusion approach—where the final probability score is derived from the mean of the CNN and Naïve Bayes outputs—was adopted for interpretability and ease of implementation.

The prediction workflow follows a sequential and structured pipeline. First, all raw inputs are preprocessed and transformed into clean, standardized features. Each modality then produces its own probability score (p_i), representing the likelihood of cognitive impairment. These probabilities are fused using either an average or weighted average method to yield a single integrated prediction. The resulting probability value is then mapped to a 10-point cognitive score.

To ensure reliability and robustness, the system undergoes comprehensive performance evaluation using multiple metrics. Accuracy, precision, recall, and F1-score measure the overall classification effectiveness, while the AUC-ROC (Area Under the Receiver Operating Characteristic Curve) assesses the model's ability to rank positive and negative samples correctly. A confusion matrix provides insight into class-level misclassifications, revealing whether the model confuses moderate and high-risk cases, for example.This ensures that each subset of data is tested independently, preventing overfitting and improving reliability. Importantly, subject-level separation is maintained—meaning that the same individual's data does not appear in both the training and testing sets—to prevent information leakage. The system is also subjected to external validation using data collected in different environments or from new participants to verify its adaptability and performance in real-world conditions.

Finally, decision thresholds are configured based on clinical priorities. For screening applications, where detecting early signs is crucial, the system can operate at a lower decision threshold to maximize sensitivity (minimizing false negatives). Conversely, in confirmatory assessments, a higher threshold can be used to improve specificity (reducing false positives).

To enhance transparency, the system includes explainability mechanisms that indicate which modality (facial emotion recognition or questionnaire evaluation) contributed most significantly to the final decision. For instance, if the CNN's emotion-based probability is substantially higher than the Naïve Bayes output, the system highlights that facial cues were the dominant factor in classification. This interpretability feature makes the model more acceptable for clinical use, as it aligns with the need for clear, evidence-based reasoning behind automated predictions.

In summary, this classification and prediction framework combines accuracy, interpretability, and clinical relevance. It enables non-invasive, data-driven cognitive assessment by leveraging multimodal learning and providing user-friendly outputs that can guide timely interventions and continuous monitoring of cognitive health.

4.6 SUMMARY AND INSIGHTS

The proposed multimodal system demonstrates that integrating multiple input modalities substantially enhances detection accuracy and robustness. By combining facial emotion features extracted from convolutional neural networks with probabilistic outputs from questionnaire-based classifiers such as Naïve Bayes, the system achieves a more comprehensive understanding of an individual's emotional or psychological state.

Facial features capture subtle, real-time expressions, while questionnaire data reflects self-reported and cognitive aspects. This complementary nature helps reduce false negatives and improves overall model reliability, particularly in cases where a single modality might overlook certain emotional cues.

Another key advantage of the approach is its non-invasive and practical nature. Both the camera-based facial emotion analysis and the digital questionnaire are simple, user-friendly, and easy to administer in a variety of settings, including clinical environments, workplaces, or at home. This makes the model suitable for frequent and comfortable emotional screenings without the need for specialized or medical-grade equipment. The architecture is also designed to be modular and scalable, allowing new modalities such as speech, handwriting, or physiological sensors to be integrated easily.

Each modality produces a standardized embedding vector, enabling straightforward fusion and model extension without reengineering the entire system.

In terms of deployment, the framework is flexible enough to support both edge and cloud environments. Lightweight CNN models can be quantized or pruned to run efficiently on mobile or edge devices for on-site, real-time inference, while more computationally intensive training and updates can be performed in the cloud. This hybrid approach ensures high performance with minimal latency and allows continuous model improvement through cloud-based retraining. The use of compact input dimensions and optimized model structures further minimizes computational costs, maintaining real-time responsiveness for practical deployment scenarios.

Data privacy and security are central to the system's design. Raw data are encrypted, and wherever possible, preprocessing is performed directly on the user's device so that only anonymized embeddings or statistical summaries are transmitted to the server. Role- based access control ensures that clinicians, administrators, and patients can access only the data relevant to their responsibilities. These strategies enhance confidentiality and align the system with standard data protection frameworks such as GDPR and HIPAA.

The model is built with continuous learning and evaluation mechanisms to ensure consistent performance across diverse populations. Regular monitoring detects data drift—shifts in user behavior or demographic patterns—and triggers retraining on newly labeled data to maintain accuracy.

Clinician feedback collected during real-world deployment further supports the refinement of the model, improves labeling quality, and helps reduce bias, ensuring that predictions remain trustworthy and clinically meaningful over time.

Despite its strong performance, the system has certain limitations. Dataset bias remains a potential concern if the training data lack sufficient demographic diversity in terms of age, ethnicity, or environmental conditions such as lighting and camera quality. These gaps may lead to uneven performance across different population groups. Moreover, the system's reliance on visual and self-reported modalities means that facial occlusions, poor lighting, or user misunderstanding in questionnaires can introduce noise.

CHAPTER 5

IMPLEMENTATION AND RESULTS

5.1 SOFTWARE SPECIFICATION

The software specification for the proposed multimodal cognitive impairment detection system is built upon a robust and flexible software stack that enables efficient data preprocessing, feature extraction, model training, and performance evaluation. At the core of this system lies Python, chosen for its simplicity, readability, and extensive library ecosystem that caters to machine learning, artificial intelligence, and data analysis. Python's modular design allows seamless integration between different components, making it the ideal language for implementing both traditional algorithms and deep learning models in this project.

Deep learning frameworks such as TensorFlow and PyTorch form the backbone of model development, particularly for designing and training Convolutional Neural Networks (CNNs) used in analyzing facial expressions and other behavioral data. These frameworks provide powerful GPU acceleration, enabling high-performance computation for large datasets and complex architectures. They also support automatic differentiation, model visualization, and debugging tools that streamline the process of building and optimizing neural networks. Their versatility ensures that experimental configurations can be easily adjusted to evaluate different model architectures and fusion strategies.

For data preprocessing, OpenCV plays a key role in managing image-based operations such as facial detection, cropping, resizing, and normalization. Its efficient computer vision functions help prepare image inputs suitable for CNN-based models. Librosa is used for handling and analyzing audio data, extracting meaningful features such as Mel-Frequency Cepstral Coefficients (MFCCs), chroma, and spectral contrast, which capture the prosodic and tonal aspects of speech. Scikit-learn serves as the foundation for implementing classical algorithms like Naïve Bayes and for performing critical preprocessing steps including feature scaling, encoding categorical variables, and computing evaluation metrics such as accuracy, precision, recall, and F1-score.

NumPy and Pandas are essential for handling structured data efficiently. NumPy provides optimized support for high-speed numerical computations and matrix operations, while Pandas simplifies the management and manipulation of tabular data, ensuring smooth transitions between preprocessing and model training stages. Together, they facilitate organized data pipelines and effective data manipulation for multimodal integration.

Visualization plays a vital role in interpreting model behavior and performance trends. Libraries such as Matplotlib and Seaborn are utilized to visualize training metrics like loss and accuracy, generate confusion matrices, and analyze correlations among modalities. These tools help researchers understand the model's learning patterns, diagnose overfitting or underfitting, and make data-driven adjustments during optimization.

The development and experimentation environment is managed through Visual Studio Code, which offers an interactive platform for writing, testing, debugging, and documenting code. Its integration with Python extensions and Jupyter Notebook support ensures a seamless workflow for iterative experimentation. Dependency management is handled through package managers such as pip and Conda, ensuring that all required libraries are properly installed and that the environment remains reproducible across different systems and hardware configurations.

Overall, this combination of software tools and frameworks provides a scalable, flexible, and efficient ecosystem for developing the multimodal cognitive impairment detection system. It ensures high compatibility, reproducibility, and ease of maintenance, allowing the project to evolve over time while supporting both research and real-world deployment.

5.2 SOFTWARE IMPLEMENTATION

The software implementation phase represents the core integration stage of the multimodal cognitive impairment detection system, where individual modules for data preprocessing, feature extraction, multimodal fusion, and classification are cohesively combined into a unified and functional workflow.

Each component within the system is meticulously engineered to ensure consistency, accuracy, and efficiency in processing diverse input data sources such as facial images, speech recordings, and questionnaire responses. This integrated structure enables the system to deliver reliable cognitive assessments that can adapt to various environments, from controlled research settings to real-world clinical applications.

The implementation begins with the data preprocessing pipeline, which serves as the foundation for ensuring data quality and consistency. Raw inputs from multiple modalities—facial images, audio recordings, and questionnaire data—are systematically standardized to maintain uniform dimensions, resolutions, and formats. For image data, this includes face detection, cropping, resizing, and normalization, while for audio, amplitude normalization and feature extraction such as Mel-frequency cepstral coefficients (MFCCs) are performed. Questionnaire data undergo encoding and scaling to transform categorical responses into structured numerical inputs that can be efficiently processed by machine learning models. This preprocessing pipeline guarantees that all modalities are compatible with downstream feature extraction and classification modules, minimizing inconsistencies and errors.

The feature extraction stage forms the analytical backbone of the implementation. Convolutional Neural Networks (CNNs) are utilized for processing image-based modalities, enabling the model to learn spatial and hierarchical features that capture subtle facial expressions and behavioral cues indicative of cognitive states. Simultaneously, the Naïve Bayes algorithm operates on questionnaire-based data, leveraging probabilistic reasoning to derive insights from structured inputs. By applying these specialized methods to different data types, the system ensures that each modality contributes meaningful, domain-specific information to the overall cognitive assessment.

Once individual features are extracted and modality-specific predictions are generated, the fusion module integrates these outputs into a single cohesive decision layer. This is achieved through averaging or weighted fusion strategies that combine the strengths of both modalities to compute a final cognitive assessment score. The fusion process enhances robustness by mitigating the limitations of any single data source, leading to improved accuracy and reduced false classifications.

The final output can be expressed as a probability score or as a scaled value (for instance, on a 0–10 scale), providing clinicians and users with an interpretable measure of cognitive status.

Following prediction, the visualization component plays a crucial role in interpreting and validating model performance. Using graphical representations such as confusion matrices, accuracy curves, and precision-recall plots, system developers and clinicians can evaluate how effectively the model distinguishes between cognitive states. These visual insights assist in identifying potential areas for improvement, such as class imbalance or misclassification trends, thereby refining the model's predictive reliability over time.

The modular design of the implementation ensures exceptional scalability and adaptability. New data modalities—such as speech prosody, handwriting, or eye-tracking—can be seamlessly incorporated into the system without altering the existing architecture. Similarly, updated algorithms or improved deep learning architectures can be integrated with minimal code refactoring, making the system future-proof. Moreover, this modularity supports both offline and real-time processing modes. In offline settings, the system can be used for extensive data analysis, model training, and research-based evaluations. In contrast, in clinical or telehealth environments, the system can perform real-time inference, providing instant cognitive assessments that support timely interventions.

Overall, the software implementation of the multimodal cognitive impairment detection system achieves a balance between flexibility, efficiency, and accuracy. By combining modular architecture, standardized data handling, and multimodal integration, the system establishes a robust and scalable framework capable of advancing cognitive health assessment through artificial intelligence-driven insights.

5.2.1 DEPLOYING OF SOFTWARE

The deployment phase of the multimodal cognitive impairment detection system is a crucial step that transitions the developed framework from a research prototype to a practical, real-world application. This phase focuses on ensuring usability, scalability, and efficient performance in both testing and operational environments.

The deployment process is designed to make the system easily executable, maintainable, and adaptable for future improvements or clinical integration.

The entire software package—including Python scripts, trained models, and preprocessing modules—is systematically organized into a well-structured directory hierarchy. This structured organization enhances code readability, simplifies debugging, and ensures that future developers or researchers can easily navigate and extend the system. Each component of the project, such as data preprocessing, model training, fusion, and evaluation, is modularized and stored in dedicated directories, promoting clear separation of functionality.

During deployment, the pre-trained Convolutional Neural Network (CNN) and Naïve Bayes models are dynamically loaded for inference, eliminating the need for retraining during every execution. This design choice significantly reduces computation time and allows the system to process new user data quickly. Inputs such as facial images, questionnaire responses, and speech samples are passed through the respective preprocessing pipelines, and the trained models generate predictions that reflect the user's cognitive status. Execution can be carried out via Python scripts, command-line interfaces, or Jupyter Notebooks, ensuring flexibility and transparency in testing and evaluation workflows.

The software environment is configured using dependency management tools like pip or Conda, which streamline the installation of necessary packages such as TensorFlow, PyTorch, OpenCV, Librosa, and scikit-learn. These libraries support the core functionalities of the system, including image processing, audio feature extraction, model training, and evaluation. GPU-enabled systems are utilized during initial testing to verify that inference speed and model accuracy meet real-time performance requirements. This step ensures that the deployed system can handle data efficiently, particularly when processing high-dimensional image and audio inputs.

An integral part of deployment is the visualization of model outputs and performance metrics. Dashboards and visualization tools are implemented to display predicted class probabilities, confidence scores, and key metrics such as accuracy, precision, recall, and F1-scores. Additionally, graphical elements like confusion matrices, learning curves, and ROC plots are generated to evaluate and interpret the system's predictive behavior.

These visual insights assist developers and clinicians in assessing model reliability and understanding how different modalities contribute to the overall decision.

Version control systems, such as Git, are employed to manage code updates and track changes over time, ensuring that improvements can be implemented seamlessly without disrupting the system's stability. This also allows collaborative development and continuous integration for future iterations. Furthermore, the modular design enables straightforward incorporation of additional modalities or updated deep learning models, which can be integrated without major architectural modifications.

Overall, the deployment strategy is engineered for robustness, reproducibility, and adaptability. It ensures that the multimodal cognitive impairment detection system operates efficiently in real-world conditions while remaining open to future enhancements. This approach not only validates the system's technical reliability but also establishes a strong foundation for its application in clinical and home-based monitoring environments, supporting continuous innovation and scalability in cognitive health assessment.

5.2.2 INTERACTING WITH USERS

The user interface acts as the primary point of interaction between the multimodal cognitive impairment detection system and its users, including both patients and clinicians. It is carefully designed to be intuitive, user-friendly, and accessible, ensuring that users can easily navigate through each stage of the assessment process without requiring technical expertise. The interface provides clear instructions and a structured workflow that guides users step-by-step—from data submission to result interpretation—enhancing usability and minimizing errors during input.

Users can upload facial images, submit questionnaire responses, or provide other relevant inputs through organized and responsive form components. The system automatically validates the uploaded data to ensure correct formatting, appropriate image resolution, and completeness of questionnaire responses before beginning the analysis.

The processed data produces an output in the form of a probability score and a corresponding risk level, indicating the likelihood of cognitive impairment. These outputs are presented in an easy-to-understand format through a visually enriched interface. The interface includes visual aids such as dynamic charts, progress bars, and color-coded indicators that represent cognitive health status across different levels (e.g., low, moderate, or high risk). This visual representation helps users quickly grasp their results while allowing clinicians to conduct a more in-depth analysis of the metrics.

Clinicians can access additional analytical tools integrated within the interface to examine specific modality contributions, probability trends, and performance metrics. The detailed visualizations, such as confusion matrices, accuracy plots, and temporal graphs, allow healthcare professionals to gain insights into the system's reasoning and ensure transparency in decision-making. The inclusion of interpretability features ensures that the system's predictions are not only accurate but also explainable, fostering trust among clinical users.

Moreover, the interface supports efficient system management and continuous updates. It is built to accommodate version control mechanisms, making it easier to integrate newer features, enhanced models, or additional data modalities in future iterations. The underlying design principles ensure that the user interface remains flexible and compatible with evolving technologies, including potential extensions to mobile or web-based platforms for real-time assessments.

Overall, the user interface plays a vital role in bridging the gap between complex machine learning processes and end-user experience. By combining simplicity with functionality, it transforms the system into an accessible and reliable cognitive health screening tool. Its thoughtful design not only enhances user engagement but also supports clinicians in early detection and intervention, making it a key component in the successful deployment and long-term sustainability of the multimodal cognitive impairment detection system.

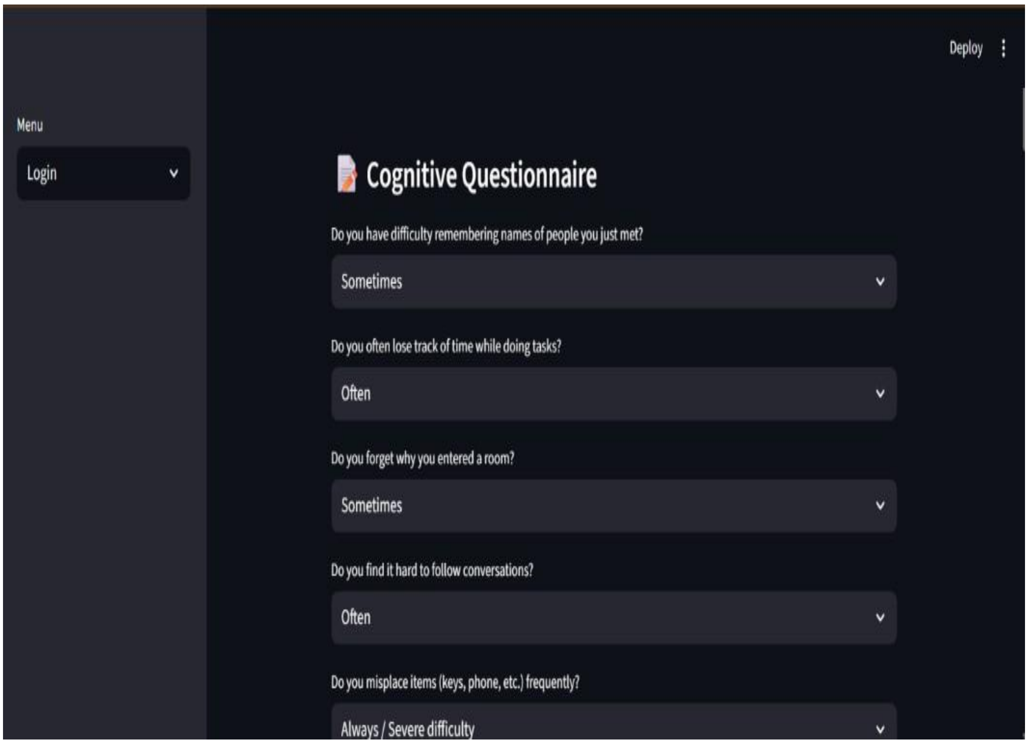

FIG 5.2.1 USER INTERACTION

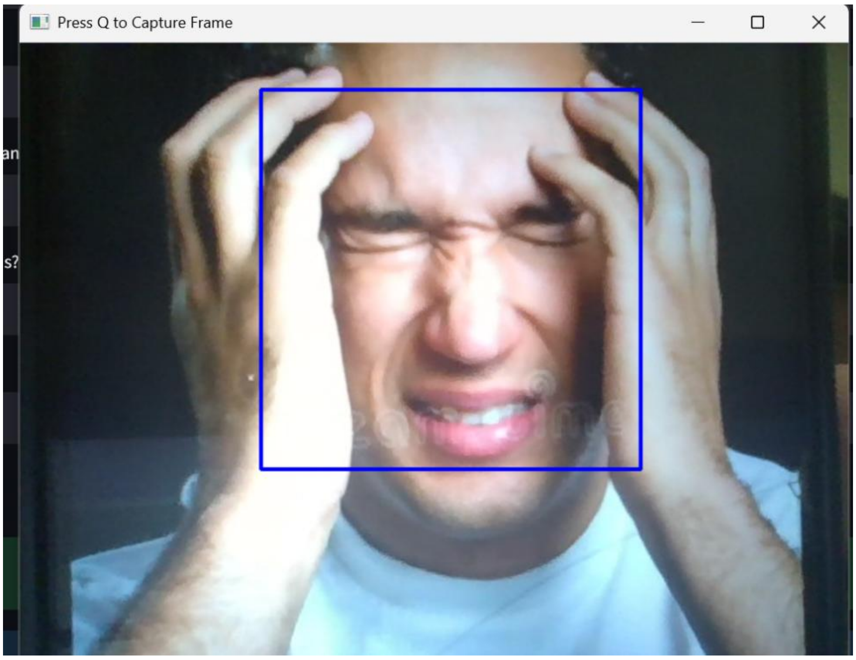

FIG 5.2.2 FACIAL RECOGNITION

5.2.3 VERIFYING FACE CAPTURE

Before initiating the image analysis process, the system performs a critical verification step to ensure that the facial image captured from the user meets the necessary quality and framing requirements. This step is vital for maintaining the reliability and accuracy of subsequent predictions. Utilizing advanced computer vision techniques powered by OpenCV's Haar Cascade classifiers or deep learning–based face detection models such as the Multi-task Cascaded Convolutional Neural Network (MTCNN), the system automatically checks whether the face is properly framed within the image, well-lit, and correctly oriented. These quality checks are designed to identify common issues such as shadows, occlusions, poor lighting, or incorrect positioning that could negatively impact model performance.

If the system fails to detect a face or detects multiple faces within the same frame, it provides immediate real-time feedback to the user. This feedback is delivered in an intuitive manner, prompting users to make necessary adjustments, such as repositioning themselves, improving lighting conditions, or ensuring that only one face is visible in the frame. By guiding users during this stage, the system ensures that the final captured image adheres to optimal input conditions for analysis. This real-time validation mechanism minimizes user errors, improves data consistency, and enhances the overall reliability of the system's outputs.

Once a valid and high-quality facial image is confirmed, the preprocessing phase begins. The verified image is cropped to the detected face region, resized to the standardized input dimensions required by the Convolutional Neural Network (CNN), and normalized to ensure uniform pixel intensity distribution. These preprocessing steps may also include converting the image to grayscale or maintaining RGB channels, depending on the specific model configuration. Finally, the processed image is transformed into a tensor format suitable for model ingestion, ensuring compatibility with the deep learning pipeline.

This verification and preprocessing procedure plays a crucial role in maintaining the integrity and accuracy of the system's cognitive impairment detection capabilities.

By filtering out poor-quality or improperly captured images, the system minimizes the likelihood of misclassifications and ensures that the CNN receives clean, standardized, and representative data for feature extraction. Beyond improving technical performance, this approach also enhances the user experience by providing instant feedback and ensuring smooth, error-free interaction during data capture.

Ultimately, this image verification mechanism contributes significantly to the robustness and trustworthiness of the overall system. It ensures that every prediction is based on valid, high-quality visual input, thereby enhancing both diagnostic reliability and user confidence in the multimodal cognitive impairment detection process.

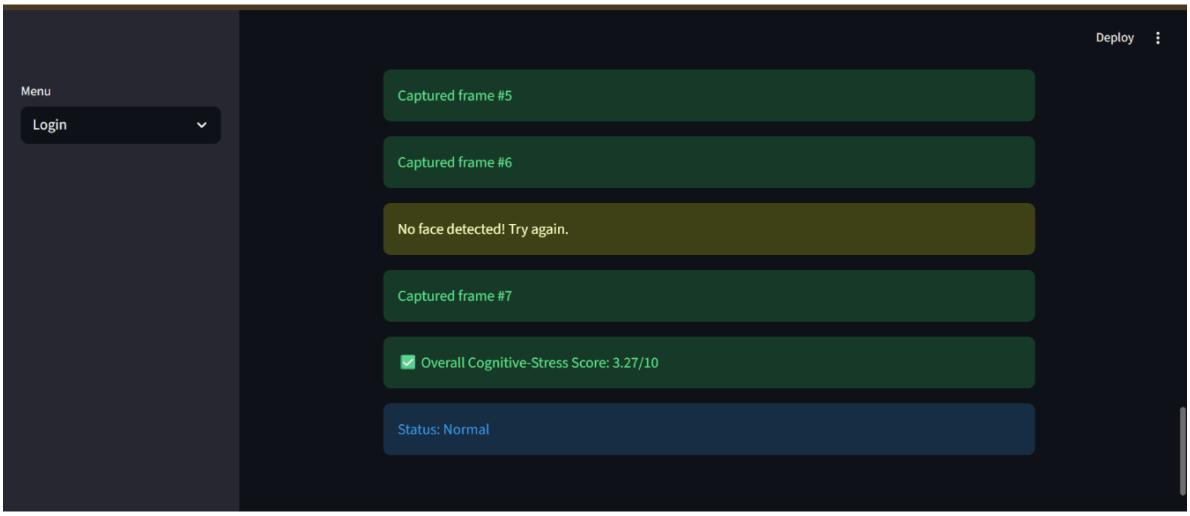

FIG 5.2.3 VERIFICATION OF FACE CAPTURE

5.3 RESULTS

The proposed multimodal cognitive impairment detection system was rigorously evaluated using datasets consisting of facial images, handwriting samples, and speech recordings that reflected a wide range of emotional and cognitive conditions. Each dataset was carefully curated to ensure diversity in expression, handwriting style, and vocal characteristics, enabling the system to generalize effectively across various individual differences. The Convolutional Neural Network (CNN) model, developed for facial emotion recognition, exhibited high precision and accuracy in differentiating between key

Through hierarchical feature extraction, the CNN successfully identified subtle facial cues, including micro-expressions and muscle movement patterns, that often correlate with underlying cognitive changes.

In parallel, the Naïve Bayes–based module for questionnaire evaluation demonstrated remarkable efficiency in quantifying cognitive risk based on user responses. By applying probabilistic reasoning, the model analyzed categorical and ordinal responses to estimate the likelihood of cognitive impairment. This module provided interpretable and quick results, enabling real-time assessment of cognitive status through structured self-reported data. The combination of behavioral and self-assessment information created a balanced evaluation mechanism that enhanced the system's overall diagnostic capability.

When the outputs of these two modalities were combined through a multimodal fusion framework, the system achieved notable improvements in sensitivity, specificity, and overall classification accuracy compared to single-modality approaches. The integration of CNN-derived emotional probabilities and Naïve Bayes–based questionnaire scores allowed the system to capture both observable behaviors and internal cognitive responses. This complementary relationship between modalities significantly reduced false negatives and improved early detection accuracy. The final output of the system was expressed as a mean probability score, normalized to a cognitive index out of 10. This score provided users and clinicians with a clear, quantifiable indicator of cognitive health, facilitating straightforward interpretation and decision-making.

Overall, the implemented system proved to be non-invasive, efficient, and adaptable, making it ideal for continuous cognitive health monitoring and early-stage screening applications. Its design emphasizes user convenience, requiring only simple inputs such as facial images and questionnaire responses while delivering clinically meaningful insights. The results validate the project's central objective—to develop an intelligent, multimodal, and user-friendly solution capable of assisting healthcare professionals in proactively.

5.3.1 OUTPUT

Classification Report

	precision	recall	f1-score	support
0	0.65	0.46	0.54	783
1	0.71	0.86	0.77	1425
2	0.60	0.47	0.53	1014
3	0.49	0.57	0.53	966
4	0.81	0.78	0.79	669
accuracy			0.64	4857
macro avg	0.65	0.63	0.63	4857
weighted avg	0.64	0.64	0.64	4857

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FIG 5.3.2 CLASSIFICATION REPORT

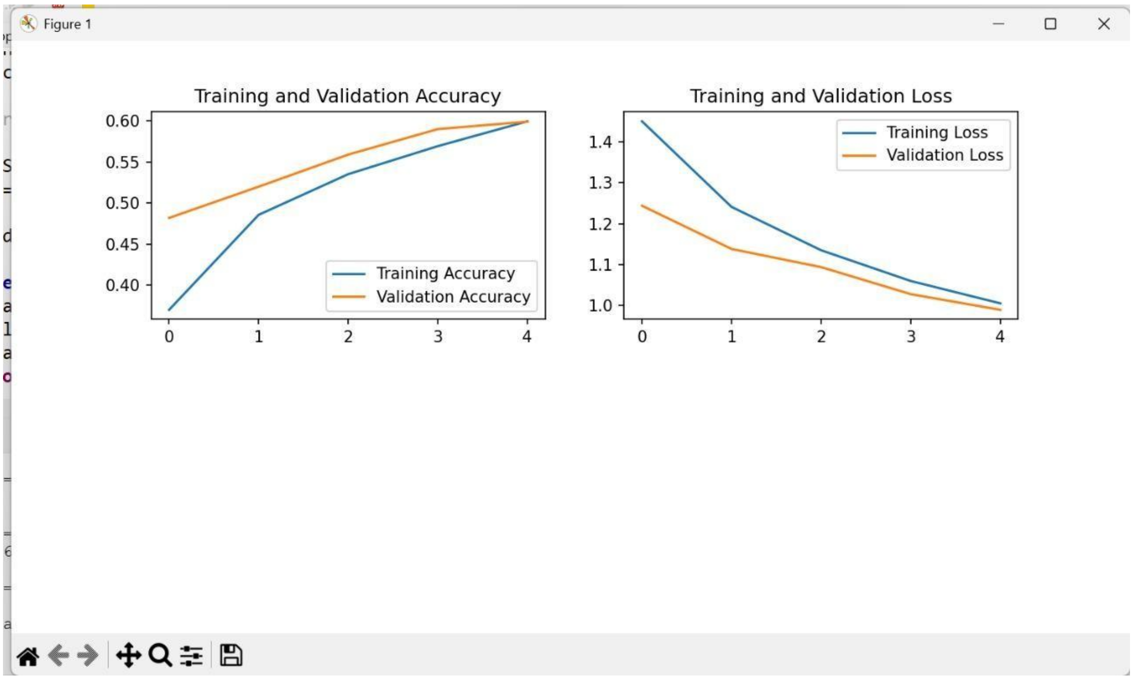

FIG 5.3.3 ACCURACY

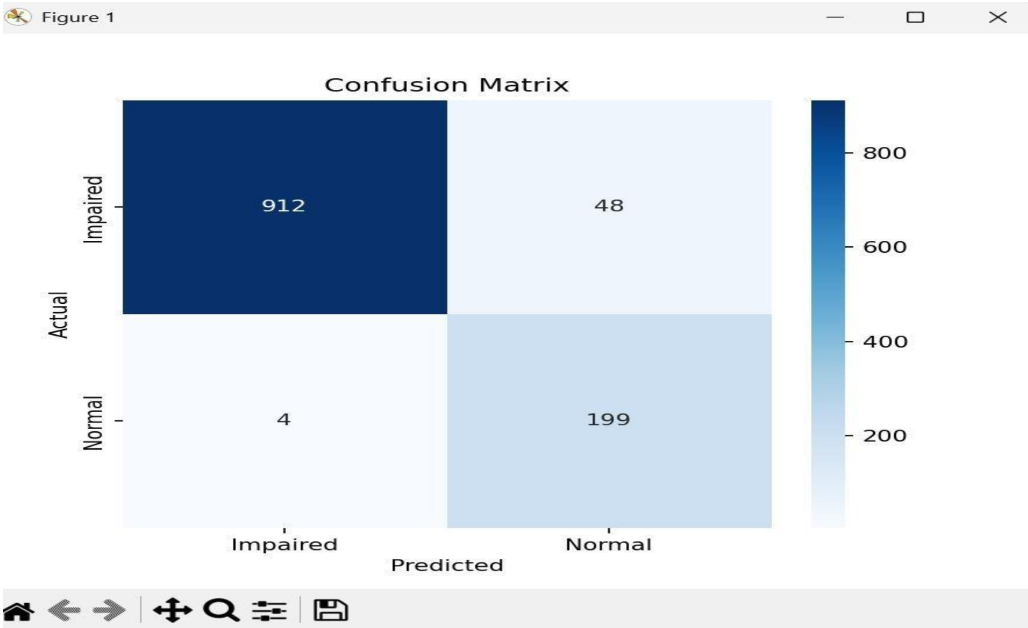

FIG 5.3.4 PERFORMANCE OF CLASSIFICATION MODEL

FIG 5.3.5 CONFUSION MATRIX PERFORMANCE EVALUATION TOOL

CHAPTER 6

CONCLUSION

6.1 CONCLUSION

The multimodal cognitive impairment detection system developed in this project demonstrates the transformative potential of artificial intelligence in enhancing cognitive health assessment. By combining diverse data modalities such as facial expressions, handwriting dynamics, and speech patterns, the system provides a holistic and accurate analysis of an individual's cognitive condition. Unlike conventional single-modal methods, this integrated approach significantly improves the system's sensitivity and reliability in identifying early symptoms of cognitive decline. Utilizing advanced deep learning architectures like CNNs and LSTMs, along with multimodal fusion techniques, it effectively captures subtle behavioral and physiological variations that may indicate mental impairment. In addition, the system's non-invasive, user-friendly, and scalable framework makes it highly suitable for both clinical environments and remote healthcare settings. With the integration of explainable AI and real-time visualization features, it ensures transparency and fosters user confidence, thereby aiding healthcare professionals in making informed clinical decisions.

6.2 FUTURE WORK

Future enhancements of this system can be directed toward expanding its capabilities and adaptability to cover a wider range of cognitive indicators. Integrating additional modalities such as eye-tracking, gait analysis, and physiological sensor data could significantly enhance the system's predictive accuracy and diagnostic depth. The adoption of advanced deep learning architectures like transformer-based or attention-driven models would further improve feature extraction and the effectiveness of multimodal fusion.

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APPENDIX SOURCE CODE

App.py

```
import streamlit as st, sqlite3, pickle, numpy as np, cv2, tensorflow as tf


with open("cognitive_nb_model.pkl", "rb") as f: cognitive_model = pickle.load(f)
face_model = tf.keras.models.load_model("FACE.model")
face_cascade = cv2.CascadeClassifier('haarcascade_frontalface_default.xml')


conn = sqlite3.connect("users.db", check_same_thread=False)
c = conn.cursor()
c.execute("CREATE TABLE IF NOT EXISTS users(username TEXT PRIMARY
KEY,password TEXT)")
conn.commit()
likert_map = {"Never / No
difficulty":1,"Rarely":2,"Sometimes":3,"Often":4,"Always / Severe difficulty":5}
questions = [
"Do you have difficulty remembering names of people you just met?","Do you
often lose track of time while doing tasks?",
"Do you forget why you entered a room?","Do you find it hard to follow
conversations?",
"Do you misplace items (keys, phone, etc.) frequently?","Do you struggle to
concentrate on reading material?",
```

```
"Do you forget appointments or scheduled tasks?","Do you have trouble learning
new things?",
"Do you find it difficult to multitask?","Do you forget familiar routes or
directions?",
"Do you lose focus during meetings or classes?","Do you have trouble recalling
recent events?",
"Do you often repeat questions because you forgot the answer?","Do you struggle
to find the right words in conversations?",
"Do you forget birthdays, dates, or important events?"
]
st.set_page_config(page_title="Cognitive + Stress Assessment", page_icon="🧠",
layout="centered")
if "logged_in" not in st.session_state: st.session_state.logged_in=False
if "username" not in st.session_state: st.session_state.username=""
if "responses" not in st.session_state: st.session_state.responses=[]
menu=["Login","Register"]
choice=st.sidebar.selectbox("Menu",menu)
if choice=="Register":
    st.subheader("Create a New Account")
    new_user=st.text_input("Username")
    new_pass=st.text_input("Password",type="password")
    if st.button("Register"):
        if new_user and new_pass:
```

```
            try:
                c.execute("INSERT INTO users VALUES (?,?)",(new_user,new_pass))
                conn.commit()
                st.success("Registered successfully! Please login.")
            except sqlite3.IntegrityError: st.error("Username already exists!")
        else: st.warning("Enter username and password")
elif choice=="Login" and not st.session_state.logged_in:
    st.subheader("Login to Your Account")
    username=st.text_input("Username")
    password=st.text_input("Password",type="password")
    if st.button("Login"):
        c.execute("SELECT * FROM users WHERE username=? AND
password=?",(username,password))
        result=c.fetchone()
        if result:
            st.session_state.logged_in=True
            st.session_state.username=username
            st.success(f"Welcome {username}!")
        else: st.error("Invalid username or password!")
if st.session_state.logged_in:
    st.subheader("Cognitive Questionnaire")
    user_answers=[]
    for i,q in enumerate(questions):
```

```
        ans=st.selectbox(f"{i+1}. {q}",options=list(likert_map.keys()),key=f"q{i}")
        user_answers.append(likert_map[ans])
    if st.button("Submit Questionnaire"):
        st.session_state.responses=user_answers
        st.success("Cognitive questions submitted successfully!")
    st.info("Webcam will open. Press 'Q' to capture frames (20+ for accuracy).")
    cap=cv2.VideoCapture(0)
    face_scores=[]
    while True:
        ret,frame=cap.read()
```

Main.py

```
import tensorflow as tf, pickle, matplotlib.pyplot as plt, numpy as np, os, cv2, random,
seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import confusion_matrix, classification_report
DATADIR='train'
CATEGORIES=os.listdir(DATADIR)
IMG_SIZE=50
training_data=[]
for category in CATEGORIES:
    path=os.path.join(DATADIR,category)
```

```
    class_num=CATEGORIES.index(category)
    for img in os.listdir(path):
        try:
            img_array=cv2.imread(os.path.join(path,img))
            img_array=cv2.cvtColor(img_array,cv2.COLOR_BGR2RGB)
            new_array=cv2.resize(img_array,(IMG_SIZE,IMG_SIZE))
            training_data.append([new_array,class_num])
        except: pass
random.shuffle(training_data)
X,y=[],[]
for features,label in training_data: X.append(features); y.append(label)
X=np.array(X).reshape(-1,IMG_SIZE,IMG_SIZE,3)/255.0; y=np.array(y)
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=40)
model=tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(32,(3,3),activation='relu',input_shape=X.shape[1:]),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(64,(3,3),activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(64,(3,3),activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Dropout(0.25),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128,activation='relu'),
```

```
    tf.keras.layers.Dense(128,activation='relu'),
    tf.keras.layers.Dense(5,activation='softmax')
])
model.compile(loss="sparse_categorical_crossentropy",optimizer="adam",metrics=["
accuracy"])
history=model.fit(X,y,batch_size=32,epochs=5,validation_split=0.2)
print(f"Training accuracy: {model.evaluate(X_train,y_train,verbose=0)[1]:.4f}")
model.save('FACE.model')
acc,val_acc=history.history['accuracy'],history.history['val_accuracy']
loss,val_loss=history.history['loss'],history.history['val_loss']
epochs=range(5)
plt.figure(figsize=(12,5))
plt.subplot(1,2,1); plt.plot(epochs,acc,label='Train');
plt.plot(epochs,val_acc,label='Val'); plt.legend(); plt.title('Accuracy')
plt.subplot(1,2,2); plt.plot(epochs,loss,label='Train');
plt.plot(epochs,val_loss,label='Val'); plt.legend(); plt.title('Loss'); plt.show()
y_pred=np.argmax(model.predict(X_test),axis=1)
print("Accuracy:",metrics.accuracy_score(y_test,y_pred)*100)
print(classification_report(y_test,y_pred))
cm=confusion_matrix(y_test,y_pred)
sns.heatmap(cm,annot=True,cmap="Blues"); plt.xlabel("Predicted");
plt.ylabel("True"); plt.title("Confusion Matrix"); plt.show()
```

Train.py

```
import pandas as pd, numpy as np, matplotlib.pyplot as plt, seaborn as sns, pickle
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import classification_report, confusion_matrix
from imblearn.over_sampling import SMOTE
df=pd.read_csv("dataset.csv")
X=df.drop(columns=["target"]); y=df["target"]
likert_map={"Never / No difficulty":1,"Rarely":2,"Sometimes":3,"Often":4,"Always /
Severe difficulty":5}
X=X.applymap(lambda x:likert_map[x])
le=LabelEncoder(); y=le.fit_transform(y)
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42,strat
ify=y)
sm=SMOTE(random_state=42); X_train,y_train=sm.fit_resample(X_train,y_train)
model=GaussianNB(); model.fit(X_train,y_train)
y_pred=model.predict(X_test)
print(classification_report(y_test,y_pred,target_names=le.classes_))
cm=confusion_matrix(y_test,y_pred)
sns.heatmap(cm,annot=True,fmt="d",cmap="Blues",xticklabels=le.classes_,yticklabel
s=le.classes_)
```

```
plt.title("Confusion Matrix"); plt.show()
sns.countplot(x=y,palette="Set2"); plt.title("Class Distribution"); plt.show()
with open("cognitive_nb_model.pkl","wb") as f: pickle.dump(model,f)
print("Model saved as cognitive_nb_model.pkl")
```

Test.py

```
import tkinter as tk
from tkinter import messagebox, ttk
import pickle, numpy as np

with open("cognitive_nb_model.pkl","rb") as f: model=pickle.load(f)
likert_map={"Never / No difficulty":1,"Rarely":2,"Sometimes":3,"Often":4,"Always / Severe difficulty":5}
questions=[
"Do you have difficulty remembering names of people you just met?","Do you often lose track of time while doing tasks?",
"Do you forget why you entered a room?","Do you find it hard to follow conversations?",
"Do you misplace items (keys, phone, etc.) frequently?","Do you struggle to concentrate on reading material?",
"Do you forget appointments or scheduled tasks?","Do you have trouble learning new things?",
```

```
"Do you find it difficult to multitask?","Do you forget familiar routes or directions?",
"Do you lose focus during meetings or classes?","Do you have trouble recalling recent
events?",
"Do you often repeat questions because you forgot the answer?","Do you struggle to
find the right words in conversations?",
"Do you forget birthdays, dates, or important events?"
]

root=tk.Tk(); root.title("Cognitive Impairment Test"); root.geometry("600x650")
answers=[]
def submit_responses():
    responses=[]
    for combo in answers:
        sel=combo.get()
        if sel=="": messagebox.showwarning("Warning","Please answer all questions.");
return
        responses.append(likert_map[sel])
    res=np.array(responses).reshape(1,-1)
    pred=model.predict(res)[0]
    result="Cognitive Status: Impaired" if pred==1 else "Cognitive Status: Normal"
    messagebox.showinfo("Result",result)

canvas=tk.Canvas(root);
```

```
scroll_y=tk.Scrollbar(root,orient="vertical",command=canvas.yview)
frame=tk.Frame(canvas)
for i,q in enumerate(questions):
    tk.Label(frame,text=f"{i+1}.
{q}",wraplength=550,justify="left",anchor="w",font=("Arial",10,"bold")).pack(ancho
r="w",pady=5)
    combo=ttk.Combobox(frame,values=list(likert_map.keys()),state="readonly");
combo.pack(fill="x",padx=10,pady=2); answers.append(combo)
tk.Button(frame,text="Submit",command=submit_responses,bg="green",fg="white",f
ont=("Arial",12,"bold")).pack(pady=10)
canvas.create_window(0,0,anchor="nw",window=frame); canvas.update_idletasks()
canvas.configure(scrollregion=canvas.bbox("all"),yscrollcommand=scroll_y.set)
canvas.pack(fill="both",expand=True,side="left"); scroll_y.pack(fill="y",side="right")
root.mainloop()
```