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Iot Based Stress Detection Using Cognitive Assistance For The Elderly

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Abstract—

Facial expressions are one of the key features of human beings that can be used to speculate emotional state at a particular moment. The current work employs Convolution Neural Network to develop a facial recognition model that categorizes a facial expression into some different emotion categories Afraid, Anger, Disgust, Happiness, Neutral, Sad, and Surprise. Capturing facial expressions over a certain period of time can give an idea of what extent the elderly is feeling pain and can enable nurse/family members to decide their feelings and provide necessary assistance. For identification, the elderly's photos are continuously taken with a smart camera and sent to the decision maker (laptop or desktop). Once the elderly are identified, he/she is monitored continuously for emotion recognition through facial expressions, and the detected emotions are stored. When an abnormal condition is detected, an alert message is sent to the caretaker/nurse. The system analyses visual cues, such as facial expressions and eye movements to detect signs of stress using computer vision and machine learning.

Keywords—cognitive assistance, machine learning, Facial expression, elderly

I.INTRODUCTION

Cognitive deficit is the most common health condition in elderly people. Approximately 5.2 million people of age 65 and older suffer from cognitive impairment. Dementia is one of the major causes of cognitive impairment which can be seen in elderly aged and more. As the population grows rapidly there is growing interest in advance technology like use of mobile phone (smartphone) for real time monitoring and many more. There are many patients and elderly people who are alone worldwide that can lead them towards stress and health deterioration, and none is there to take care of them as they may require help in that stage of life. Therefore, it is important to take preventative measures and use technologies that can aid in early detection. However there are many benefits to detect the cognitive symptoms early and accurate so that it can be cured.

Human facial recognition is widely used in human- computer interaction to analyse and understand the emotions of human. As per the research paper [22], the highest percentage of emotional data shown by facial expression is 55%. Emotions are simply a human state of mind that corresponds to mood. These sentiments are typically distorted by motivation, attitude, temper, character, and temperament.

The integration of IoT technology into healthcare systems has resulted in novel ways for monitoring and improving well-being of senior adults. One such breakthrough is the IoT-Assisted Context-Aware Automatic Cognitive Health Assessment, which uses machine learning models like Decision Trees, Random Forests, and Support Vector Machines to provide real-time mental health monitoring. It uses a Hierarchical Dynamic Bayesian Network (HDBN) model to recognize emotions and provide actionable insights for comprehensive mental health tracking [1].

Similarly, the IoT-Based Remote Healthcare Monitoring System Through Emotion Recognition focuses on facial expression analysis to assess emotional states. The system uses image processing and methods such as Support Vector Machines (SVM) and confusion matrices to transmit real-time alert messages to caregivers. Despite its prospective applications, the system confronts obstacles such as emotional misunderstanding and a lack of clinical validation [2].

Artificial Intelligence for Cognitive Health Assessment: State-of-the-Art, Open Challenges, and Future Directions [9] presents the role of AI in diagnosing cognitive illnesses including dementia and Alzheimer's disease. The paper further delivers into the ethical and legal constraints of applying AI in healthcare, emphasizing the importance of secure data handling and balanced datasets for improving diagnostic accuracy and dependability.

The Smart Wristband-Based Stress Detection Framework for Older Adults [11] use cortisol as a stress biomarker, is a wearable system that integrates several physiological inputs, including electrodermal activity (EDA), blood volume pulse (BVP), and skin temperature (ST). A random forest classifier improves the accuracy of stress categorization, and the framework incorporates a voice-based interface to encourage user interaction and self-monitoring. Limitations included the necessity for frequent sensor calibration and probable inaccuracies caused by environmental conditions.

The current literature collectively demonstrate the transformational potential of IoT and AI technologies in healthcare, notably for improving cognitive and emotional well-being among the elderly. These frameworks enable novel healthcare solutions by utilizing real-time data, powerful machine learning algorithms, and wearable sensors. This study investigates the practical implementations, problems, and future potential for building IoT-based stress detection systems for cognitive aid, focusing on their role in establishing a more inclusive and responsive healthcare environment.

II. LITERATURE REVIEW

Table 1: Problems addressed and gaps identified in related work

Citation	Objective	Gap Identified and future scope
[1]	Recognition based on a Hierarchical Dynamic Bayesian Network (HDBN) mode	Assess other mental health conditions such as anxiety, depression, and dementia, allowing comprehensive mental health tracking and diagnosis.
[2]	Image processing, frame rate comparisons and SVM, confusion matrix and an alert SMS message	Emotional Misinterpretation Lack of Clinical Validation
[3]	Use of ECG for detection and classification emotion.	Potential issues with emotion recognition accuracy.
[4]	It provides an affordable option for ongoing health monitoring by increasing the decision-making precision	To improve reliability, expand to include more health metrics and sophisticated algorithms.
[5]	It focuses on the non intrusive, real-time monitoring of elderly people with mental health conditions	Continued surveillance and data gathering privacy issues
[6]	The project is to improve real-time health monitoring and boost caregiver productivity to improve healthcare services	The prototype's scalability is hampered by its lack of interface with healthcare system
[7]	The automated chatbot assesses users' topic descriptions and detects cognitive impairment using machine learning.	The majority of existing methods rely on human supervision for early diagnosis and are based on manual assessments.
[8]	Robots can enhance the health and psychological well-being of elderly people	Focus on long-term effects of social robots
[9]	These evaluations are commonly employed in the diagnosis and follow-up of disorders	Improve data privacy through secure handling methods. Increase data quality with larger, balanced datasets.
[10]	It addresses IoT healthcare issues, specifically those related to security and data management	The main disadvantages include high power consumption, security holes caused by dangers associated with data
[11]	Using cortisol as a biomarker for stress detection in older persons, the study presents a smart wristband architecture	Future research could improve the prototype by adding more physiological biomarkers
[12]	The framework uses the Restricted Boltzmann Machine (RBM) algorithm	The framework's emphasis on negative emotions

[13]	Integrated Smart Home Systems acceptability variables including comfort and perceived benefits	Non-wearable sensors to reduce discomfort and complexity
[14]	Use sensors to measure environmental and health variables and provide timely alerts.	enhancing user interfaces, investigating non-invasive monitoring, and advanced analytics
[15]	It focuses on creating IoT solutions for the home that monitor and support health	Progress technology to overcome obstacles like security threats and privacy issues.

Table 1 highlights important developments and approaches in the field as it investigates the relationship between stress detection and cognitive support. It presents IoT and machine learning approaches to improve the effectiveness and performance of stress detection systems for elderly. Costa et al. [3] investigate cognitive assistant frameworks that rely on machine learning and human-computer interaction techniques. Their study focuses on designing intuitive interfaces for elderly while taking into account their cognitive limitations. The study is consistent with the increased demand for low-cost assistive technology that help the elderly while also fostering independence.

Isa et al. [4] created an IoT-based health monitoring system that uses fuzzy logic to track vital signs in elderly patients, specifically blood oxygen saturation and heart rate. The system uses fuzzy rules to determine stable versus unstable conditions, however it is confined to monitoring only two metrics. The authors acknowledge that sensor accuracy in non-controlled conditions remains a difficulty, recommending that future research should include more health metrics and create algorithms to improve reliability.

Raed et al. [5] propose an RFID-based system with wearable sensors to monitor elderly patients' movements and mental stress using physiological signals. While novel in its approach to non-intrusive monitoring, the system has limits in situations with low RFID signal strength and raises privacy issues about continuous position tracking.

UWIZEYIMANA [6] describes an Internet of Things-based health monitoring prototype for senior care in Rwanda that measures body temperature, heart rate, and location data. The system promises to improve healthcare services in rural areas, however it does not integrate with existing healthcare infrastructure. The author underlines the importance of establishing a comprehensive IoT architecture that interfaces easily with existing healthcare systems.

de Arriba-Pérez et al. [7] provide an intelligent conversational platform that use natural language processing to assess cognitive loss in seniors. The technology uses automated chatbot conversations and machine learning algorithms to differentiate itself from standard diagnostic methods by providing autonomous assessment capabilities.

Javed et al. [9] examine the impact of assistive social robots in elderly care, focusing on companionship elements. Their findings show scant evidence of positive impacts, highlighting cultural bias in existing research and the need for more robust, long-term investigations across varied cultures.

Zamanifar and Azadeh [10] investigate IoT-based healthcare systems, dividing them into edge computing and traditional IoT healthcare techniques. Their findings emphasize security and data management problems, as well as future approaches in serverless computing for improved system performance.

Fonseca et al. [12] create a system for tracking geriatric emotions during multimedia encounters, attaining 90% accuracy in identifying six basic emotions. The system employs heart rate data and the Restricted Boltzmann Machine algorithm, however it is limited by its emphasis on negative emotions and the possibility of external interference with heart rate measurements.

Jo et al. [13] use focus group interviews to explore the elderly's impressions of Integrated Smart Home Systems. Their findings show that, while privacy problems exist, elder users often accept these technologies because of the perceived benefits of constant monitoring. The study's drawbacks include a small, female-only sample size, indicating the need for more varied participant groups in future studies.

Sonia and Semwal [14] investigate IoT applications in geriatric care, specifically indoor health monitoring systems. Their research looks on how sensors can measure numerous health indicators and environmental elements and send timely notifications to caretakers. The authors acknowledge limitations in sensor accuracy and technological acceptance among senior users, and suggest that future research should focus on enhancing user interface design and non-invasive monitoring techniques.

Edoh et al. [15] investigate IoT applications for aiding elderly people with dementia using in-home monitoring systems. While their research shows potential benefits for improving quality of life, they also identify substantial issues in data security and privacy protection, recommending that future research address these concerns while investigating novel IoT applications in the elder healthcare.

Lourenço et al. [16] investigate IoT-based solutions for geriatric health monitoring, with a special emphasis on systems intended to improve quality of life. Their research emphasizes the importance of continued technology advancement while recognizing security threats and privacy concerns as major implementation obstacles.
Lee et al. [17] investigate smart house and ambient assisted living systems that include IoT devices for senior care. Their research stresses user-centered design concepts while emphasizing that technology adoption is sometimes difficult for those with cognitive disabilities. The authors propose bridging the gap between technology and human care using holistic methods.

Sinha et al. [18] provide a review of emotion recognition technology in elder care, with a focus on computer vision and machine learning advances. Their research looks into several detection approaches using facial expressions and physiological cues, while also highlighting implementation issues such as high prices and low adoption rates.
Jiang et al. [19] investigate contactless detection techniques for monitoring emotional expressions and cognitive health in elders. Their findings highlight the significance of emotional recognition in assessing cognitive health, specifically how impaired emotional recognition abilities might lead to social disengagement.

Al-Shaqi et al. [20] present a thorough examination of ambient aided systems for independent senior living. Their findings emphasize the relevance of social connection elements in these systems, as well as how technology might help seniors interact with their support networks.
Muhammad et al. [21] examine facial recognition systems, with a special emphasis on deep learning algorithms and CNNs for emotion detection. Their review underlines the importance of multiple training datasets for improving algorithm generalizability and investigating various emotion recognition methodologies.
Dalvi et al. [22] investigate the progression of machine learning techniques for facial emotion recognition, from traditional algorithms to advanced deep learning methods. Their work emphasizes the move from subjective interpretation to automated methods while recognizing the ongoing issues of accuracy and execution.
Prete et al. [23] investigated implicit and explicit facial emotion recognition across age groups, establishing essential concepts in emotion processing. Their research looks at methodological techniques, emphasizing the need of including both conscious and unconscious emotional responses in detection systems.
Chen et al. [24] investigate IoT applications in smart health monitoring for elderly, with an emphasis on indoor environmental parameters and health metrics. Their findings acknowledge issues in sensor accuracy and system reliability, while also suggesting improvements in user interface design and monitoring methodologies.

Ali et al. [25] investigate IoT technology applications for dementia sufferers, specifically home monitoring systems and support mechanisms. Their research identifies security and privacy issues, while underlining the importance of continued technological innovation in elder healthcare solutions.
Costanzo et al. [26] examine IoT-based monitoring systems for senior dementia patients, with an emphasis on improving their quality of life. Their findings highlight implementation issues such as security hazards and privacy concerns, and they recommend that future study address these limits while investigating new applications.
Patel et al. [27] investigate sensing technologies for Alzheimer's disease care, emphasizing the preference for non-intrusive sensors over wearable devices. Their research advises using digital twin technologies and AI for individualized therapies, while also recognizing the underutilization of developing technology.
Kshirsagar et al. [28] investigate AI-based assistive solutions for senior care, namely their usefulness in minimizing isolation. Their findings suggest that, while these technologies show potential, they cannot completely replace human interaction. The authors underline the need of combining neuroscientific methods with diverse approaches to technological growth.
Nath et al. [29] describe an intelligent remote health monitoring system (i-MsRTRM) based on IoT and GSM technologies. Their work addresses cost issues in current monitoring systems while acknowledging limitations in tracking capability. The authors propose that future developments should focus on incorporating new health measures while remaining cost-effective.
Setz et al. [30] create a mobile healthcare monitoring system for real-time physiological data collection. While unique in its approach to remote monitoring, the system has limits in terms of complete health tracking and internet access requirements. The authors advocate investigating various sensor integration and increased data encryption approaches.
The Fer2013 dataset was used by Gao and Zhiming [31] to assess Convolutional Neural Networks and Residual Networks for facial expression recognition. Their analysis demonstrates that CNN has an advantage in the short run, but it also suggests that ResNet's architecture may have long-term benefits. The work acknowledges the constraints of dataset diversity and suggests studying alternate designs such as Transformer-based models.
Khaireddin et al. [32] use VGGNet architecture and hyperparameter optimization to improve facial emotion identification accuracy on the FER2013 dataset. Their research achieves 73.28% accuracy without extra training data, although there are still issues in dealing with intraclass variations and small expression changes.

Debnath et al. [33] offer the "ConvNet" model for seven-emotion recognition, which combines CNN and LBP characteristics. Their technique yields good accuracy rates on the JAFFE and CK+ datasets, but it has limits in real-world applications due to lighting differences and demographic representation.
Białek et al. [34] proposed two CNN models for facial emotion identification, emphasizing efficiency and ensemble techniques. While improving performance with fewer resources, their work recognizes real-world constraints and recommends using multimodal data sources for greater accuracy.
Yaermaimaiti et al. [35] present a unique face expression recognition approach that combines DLDP and AR-LBP characteristics with CNN classification. Their approach enhances recognition rates while preserving real-time performance, although there are limits in dealing with different illumination situations and occlusions. The authors recommend investigating integration with additional sensory modalities to improve accuracy.

III.IMPLEMENTATION

The current study utilizes the FER2013 dataset [36] and aligns with findings from recent research emphasizing the superior performance of Convolutional Neural Networks (CNNs) in emotion recognition tasks, particularly for understanding stress levels in older adults. The following research papers provide a strong foundation for this conclusion:

• **"Comparison of CNN and ResNet Neural Networks on the Performance of Facial Expression Recognition" [31]**: This study demonstrates a testing accuracy of 73.28% on the FER2013 dataset using a VGG-based CNN model, achieving one of the highest single-network accuracies without additional training data. The research underscores the computational efficiency and feature extraction capabilities of CNNs, significantly outperforming traditional methods like Support Vector Machines (SVM) and k-Nearest Neighbors (KNN).

• **"Facial Emotion Recognition: State of the Art Performance on FER2013" [32]**: Similarly, this research validates the testing accuracy of 73.28% on the FER2013 dataset using a VGG-based CNN, highlighting the advantages of CNNs over SVM and KNN in terms of performance and efficiency.

• **"Four-layer ConvNet to Facial Emotion Recognition with Minimal Epochs" [33]**: Using the FER2013 database, this study achieved a test accuracy of 61.7% with a four-layer CNN model, demonstrating the robustness of CNNs in identifying facial expressions compared to conventional approaches.

• **An Efficient Approach to Face Emotion Recognition with Convolutional Neural Networks" [34]**: This work presents a comparative analysis of CNN-based FER techniques, conclusively showing that CNNs are more accurate and efficient than traditional algorithms such as SVM and KNN.

• **"Research on Facial Expression Recognition Based on an Improved Fusion Algorithm" [35]**: This study highlights the enhanced facial feature extraction capabilities of CNNs through multi-feature fusion, further establishing their superiority over conventional methods for emotion recognition tasks.
In the current research, three machine learning models—Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN)—were constructed and evaluated on the FER2013 dataset to determine the most effective approach for stress detection. Consistent with the findings of the aforementioned studies, CNN emerged as the most accurate model, affirming its suitability for developing a robust stress detection framework.

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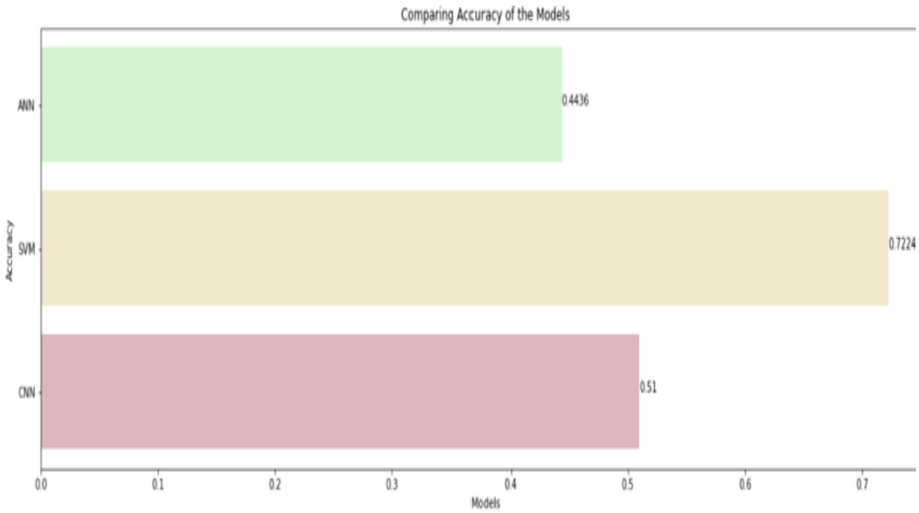

Fig 1. Comparing accuracy of the model

The development of the stress detection system, leveraging the FER2013 dataset [36], involved a systematic pipeline of data preprocessing, model training, and real-world integration. The approach aligns closely with methodologies detailed in contemporary research on CNN-based facial emotion recognition systems:

Data Preprocessing and Standardization: Consistent with the best practices highlighted in research such as "Comparison of CNN and ResNet Neural Networks on the Performance of Facial Expression Recognition" [31], the initial step involved resizing images from the FER2013 dataset to ensure compatibility with CNN input requirements. Pixel value normalization was performed to standardize the input data, thereby enhancing training efficiency and consistency, as supported by findings in "An Efficient Approach to Face Emotion Recognition with Convolutional Neural Networks" [34].

Model Training and Optimization: Following preprocessing, the dataset was divided into training and testing subsets. Using TensorFlow, a widely recognized framework for deep learning, a CNN model was trained, incorporating techniques such as dropout regularization to mitigate overfitting. This aligns with approaches in "Four-layer ConvNet to Facial Emotion Recognition with Minimal Epochs" [33], which emphasizes the significance of training optimization for robust performance. Bottleneck feature extraction, integrated into the pipeline, further streamlined the training process and enhanced accuracy.

Analysis and Visualization: Tools like Matplotlib and Seaborn were employed to monitor training progress and visualize performance metrics, a practice validated by "Research on Facial Expression Recognition Based on an Improved Fusion Algorithm" [35], which emphasizes the role of visual insights in refining model architecture and hyperparameters.

Real-Time Integration and Image Processing: To enable real-time emotion recognition, OpenCV was incorporated into the system for efficient facial detection and consistent input scaling. Such integration aligns with strategies in "Facial Emotion Recognition: State of the Art Performance on FER2013" [32], where preprocessing and input consistency were critical to achieving high accuracy.

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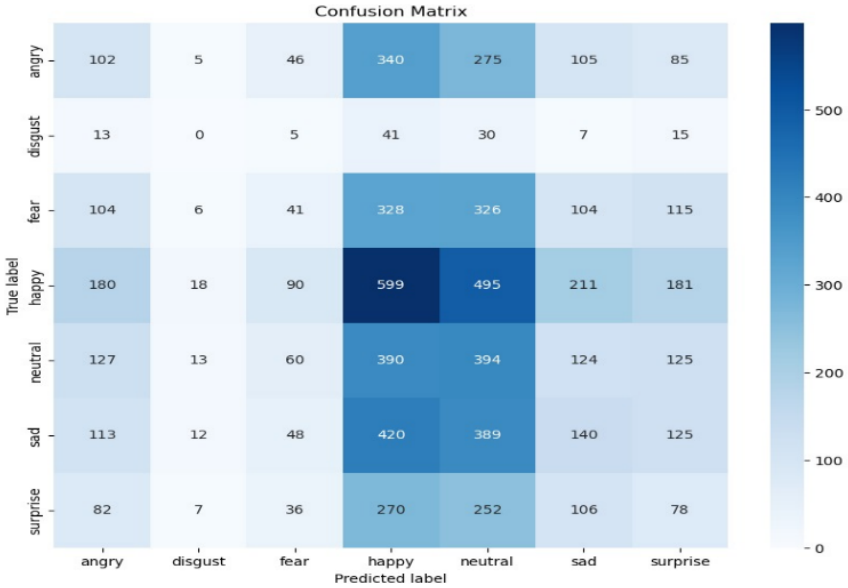

Fig 2. Confusion Matrix of the model

System Capabilities and Deployment: The trained CNN model, demonstrating high accuracy in recognizing facial expressions, became the cornerstone of the stress detection system. The system was further integrated into an Internet of Things (IoT)-based senior cognitive support framework, performing the following tasks:

1. Emotion Recognition: Identifies emotions from live or recorded facial images, consistent with findings in "Comparison of CNN and ResNet Neural Networks on the Performance of Facial Expression Recognition" [31].

2. **Stress Level Analysis**: Links recognized emotions to predefined stress thresholds, offering an evidence-based approach for analyzing stress levels.

3. Stress Management Suggestions: Provides personalized recommendations for stress alleviation tailored to senior users, as suggested in "Research on Facial Expression Recognition Based on an Improved Fusion Algorithm" [35].

By synthesizing methodologies from state-of-the-art research and implementing advanced techniques in preprocessing, model training, and deployment, this system presents a robust framework for emotion recognition and stress analysis, with applications in enhancing senior cognitive support systems.

Fig 3. Emotions

Output of the above emotion through the model:

```
Webcam accessed successfully.
Image captured successfully.
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 292ms/step
Detected Emotion: Happy
Stress Level: Low Stress
Suggestion: Keep up the good mood by engaging in enjoyable activities.
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Fig 4. Output of the happy emotion

IV. CONCLUSION

The importance of facial recognition and machine learning in creating cognitive support systems for stress detection in the elderly is highlighted by this study. The suggested framework offers a non-invasive and effective method for real-time emotional state monitoring by using facial expressions as the main input. The method enables continuous and automatic emotion detection by classifying emotions into discrete categories, including Afraid, Anger, Disgust, Happiness, Neutral, Sad, and Surprise, using convolutional neural networks (CNNs). This feature facilitates prompt actions in response to signs of stress or distress and improves caregivers' capacity to evaluate the emotional health of senior citizens.
The usefulness and scalability of this architecture are further highlighted by the incorporation of Internet of Things (IoT) technologies. Continuous monitoring is made possible by IoT-enabled smart cameras and decision-making systems, and timely contact with family members or caregivers is ensured via automatic warnings during unusual circumstances. The promise of such interdisciplinary techniques, which combine artificial intelligence (AI) with the Internet of Things (IoT), to improve healthcare solutions is supported by existing literature. Examples of these models include wearable stress detection devices and hierarchical dynamic Bayesian systems.
This study does, however, recognize a number of difficulties, such as the requirement for thorough clinical validation, sensor calibration, and data security. Due to these difficulties, algorithms must be further improved in order to increase accuracy, handle privacy issues, and provide user-friendly interfaces designed with the senior population in mind. Enhancing system robustness through the integration of multimodal inputs (such as speech and physiological signals), the incorporation of varied datasets, and compatibility with current healthcare infrastructures should be the top priority for future research paths.
To sum up, the suggested approach is a major step toward developing an inclusive and adaptable healthcare environment for senior citizens. This technology has the ability to enhance the quality of life for senior citizens while offering comfort to their relatives and caregivers by tackling existing constraints and using a multidisciplinary approach.

V. FUTURE SCOPE

The proposed framework for stress detection in elderly individuals has significant potential for enhancement through the integration of additional parameters and cognitive engagement features. To increase the accuracy and dependability of the system, a possible direction for future research is to include voice analysis as a supplementary parameter in addition to face recognition. Together with facial expressions, speech characteristics like tone, pitch, and cadence can provide deep emotional insights that help provide a more complete picture of stress levels. In real-time situations, this multimodal method will allow for more accurate and reliable stress detection.
Furthermore, the system may be expanded to incorporate a customized chatbot intended to improve senior users' cognitive capacities. This chatbot will retrieve current news via APIs and provide consumers succinct, pertinent extracts. The chatbot can improve memory recall and cognitive stimulation by having users read and respond to context-specific questions based on the news. This interactive element encourages mental agility and active engagement in addition to helping to assess cognitive health.
The goal of these developments is to provide a comprehensive approach that proactively treats cognitive impairment in older individuals in addition to identifying stress. While providing useful resources for caretakers, this interdisciplinary approach has the potential to greatly enhance the quality of life for senior citizens.

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