International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Secure IOT Assistant Based System for Alzheimer's Disease

Jishna N V[1], Dini Davis[2]

[1]PG Student, Dept. of Computer Science and Engineering, IES College of Engineering and Technology, Kerala Technological University, Chittilappilly, Thrissur

[2]Assistant Professor, Dept. of Computer Science and Engineering, IES College of Engineering and Technology, Kerala Technological University, Chittilappilly, Thrissur

ABSTRACT:

Alzheimer's disease is a neurological condition that gradually impairs a person's capacity for thought and memory. Gradually, it gets worse until it becomes a major hindrance to the way the person with the illness lives and functions in the world. The purpose of this research is to create a prototype for mild to moderate AD that provides safe information transmission and support services, allowing a family member to investigate it and safeguard the AD patient. The wearable prototype can distinguish between family and non-family members in recognized images and give a vocal communication with the individual's name. Additionally, the prototype makes it possible to track the AD person's location. The prototype makes their daily lives easier. Thus far, the prototype follows the individual with AD around and notifies caregivers of their whereabouts so that, if the patient leaves the house, they can securely return them home. Additionally, by detecting dampness, this prototype informs the patient's caregiver of their excrement. So, the prototype will help the patient in their daily life very efficiently.

KEYWORDS*:* AD, Machine learning, LBPH, classification, security, facial recognition, GPS Location, Wetness sensing, IoT.

1. INTRODUCTION

Alzheimer's disease (AD) is an incurable neurological disorder that disproportionately affects the elderly population. After examining brain tissue from a patient who had died of an undiagnosed mental illness, Alois Alzheimer first characterized it in 1906. According to estimates from the Alzheimer's Association, 13% of adults over 65 in developed countries suffer from the disease, making it the fifth most prevalent cause of mortality for those in this age group. According to World Health Organization (WHO) projections, the disease will become twice as common in the world over the next three decades, with an estimated 114 million cases by 2050. This would have a huge social impact as well as surely put further financial strain on healthcare systems around the world.

Alzheimer's disease usually develops slowly for a while before advancing progressively over a period of years. Most parts of the brain eventually suffer damage from Alzheimer's. Memory, reasoning, judgment, language, problem-solving, personality, and movement may all be impacted by the illness. Alzheimer's disease is related with five stages. These comprise mild cognitive impairment brought on by Alzheimer's disease, mild dementia brought on by Alzheimer's disease, and preclinical Alzheimer's disease. Both mild and severe Alzheimer's disease-related dementia are present. Dementia is a term used to describe a group of symptoms that impair social and intellectual functioning to the degree where they interfere with daily activities. Everybody is affected by Alzheimer's signs and symptoms in a different way.

Alzheimer's disease is a degenerative brain illness that might take years or even decades to manifest symptoms. The disease starts before symptoms develop. Tau proteins undergo structural organization and change of shape to form amyloid plaques and neurofibrillary tangles, which can be detected by new imaging tools. Clinical trials are designed to find out whether treating individuals with preclinical Alzheimer's may prevent or slow the emergence of symptoms. Determining these early changes is essential to these trials. The development of novel treatments has increased the importance of imaging technologies. Further biomarkers discovered in blood tests may suggest a higher chance of developing the illness, confirming the Alzheimer's diagnosis. Although they are not advised for everyone, genetic testing can also reveal a higher risk of Alzheimer's disease developing in its early stages. Although they are not advised for everyone, genetic testing can also reveal a higher risk of Alzheimer's disease developing in its early stages. The importance of these methods, biomarkers, and genetic testing will rise as Alzheimer's disease treatments are created.

Alzheimer's disease is typically discovered in its mild dementia stage, when symptoms significantly impair day-to-day functioning. Among the symptoms are recent event memory loss, difficulties with complex tasks, problems addressing problems, and sound judgment. A quieter or more reserved manner, less motivation to complete tasks, difficulties organizing and articulating thoughts, and difficulties locating misplaced or forgotten items are further examples of personality changes. These symptoms can lead to poor decision-making, difficulty planning family gatherings, and difficulty managing finances. In addition, people may struggle to organize and articulate their thoughts as well as to find the right words to describe various items. People often misplace or lose pricey items during this era.

People with Alzheimer's disease who are in the intermediate dementia stage require more help with everyday tasks and self-care due to their growing confusion and forgetfulness. When there are voids in their story, they frequently repeat or invent stories, exhibiting poor judgment, disorientation, and even memory loss. In addition, they could become uncontrollable when it comes to their bowel or bladder motions and require assistance with everyday tasks like showering and clothes selection. Additionally, they could have substantial behavioural and psychological changes, such growing suspicious of people or hearing or seeing things that aren't there. In addition, they could act aggressively physically and get restless or irritated, especially late in the day.

Severe dementia, the final stage of Alzheimer's disease, is characterized by a progressive loss of mental function and physical impairment. Individuals encounter a reduction in their physical capabilities, a loss of communication, and daily support with personal care activities. Without help, they might have trouble holding their heads up, walking, sitting, and even swallowing. Reflexes may become aberrant and muscles may stiffen up. They might eventually become unable of controlling bowel and bladder movements. A lack of control over bladder and bowel functions, daily assistance with everyday duties, and a reduction in speech are the hallmarks of this stage of dementia.

This research suggests an integrated approach that combines Internet of Things (IoT) technology, image processing, embedded system hardware, and machine learning. Creating a prototype that aids individuals with mild to severe Alzheimer's disease is the goal of this project. In order to enable a family member to look into and safeguard the AD patient, it also offers psychological support services and guarantees secure data transmission. This approach offers an efficient and programmed system to alleviate the suffering of those who endure it. And can take charge of their daily schedules and well-being. Thus, it develops an assistance-based prototype with face recognition and security tools to help Alzheimer's patients and improve their lifestyle. In this context, using our prototype, the person with AD will have the ability to identify family members with the help of voice communication. Additionally, a monitoring system for the patient's family members to monitor and safeguard the patients. Two other features provided by our solution concern sending notifications when the patient with AD gets panicky and about their excretion.

2. RELATED WORK

The works that are connected to our paper are briefly described in this part. Two research categories are mentioned in the literature. The first group concentrated on identifying AD, whereas the second one concentrated on helping those who had AD.

A suggestion for an early disease detection application is presented in this study. Our application consists of two steps: Using the Region of Intert ROI, segmentation was able to extract the three areas, which were the Corpus Callosum and Hippocampal Cortex. The next phases in the classification process are SVM (Support Vector Machine)-based and include Frontal region (also known as coronal region): This incision displays the front side of the brain. The plane opposite the sagittal and axial incisions is where it is obtained. In this part, we used the hippocampus region's variation descriptors. The brain is seen from above in an axial, or transverse, cup. It's associated with a plane perpendicular to the stationary magnetic field. In our work, we are interested in the cortical variation descriptor. The plane that contains the sagittal cup and the interhemispheric plan are parallel. These are side views of the brain. We were able to retrieve the Corpus Callosum variation descriptors after the segmentation step. In this case, each component was classified using the Support Vector Machine (SVM), and the final conclusion was made using a decision tree[1].

Pathophysiology-based disease biomarkers may provide objective data for disease diagnosis and staging in Alzheimer's disease (AD), a progressive neurodegenerative disorder. FDG-PET metabolic images and neuroimaging scans produced from MRIs can be used to evaluate glucose metabolism in a living brain in vivo. Several unique imaging methods that each offer complementary information are thought to combine to potentially improve the early diagnosis of AD. In this work, we provide a novel deep learning-based framework for the discrimination of AD patients using a multimodal and multiscale deep neural network[2]. The proposed framework consists of two main steps: preprocessing images, which involves dividing gray matter segmentation from MRI and FDG-PET images into patches of different sizes and extracting features from each patch; and classification, which involves training a deep neural network to find patterns that differentiate AD individuals and using the learned patterns for individual classification[2].

Describe two deep learning models based on multimodal fusion that process audio and ASR-transcribed speech simultaneously to assess the severity of Alzheimer's disease in speakers participating in a structured diagnostic test. Our best model, a BiLSTM with highway layers, achieves 84% accuracy with words, word probabilities, disfluency characteristics, pause information, and various acoustic data. Our models perform better than word-only models when using the multimodal approach that incorporates word probabilities, disfluency, and pause information, despite the fact that predicting cognitive deterioration is more challenging. Moreover, we show that multimodal fusion and gating can handle noisy inputs from acoustic characteristics and ASR hypotheses, and they offer notable advantages for AD classification[3].

Research findings indicate that Convolutional Neural Networks (CNN), which are considered deep learning approaches, outperform the machine learning techniques now in use [4]. The three main layers of a traditional CNN are the convolutional layer, pooling layer, and fully connected layer. This paper proposes an end-to-end CNN-based framework with detailed steps starting from image acquisition landing at AD-classification to classify scanned MRI images to predict whether or not they have Alzheimer's disease, and to what degree. It does this by using a machine learning application with the help of digital image processing. In digital image processing, adaptive thresholding modifies the threshold dynamically for every pixel, in contrast to traditional techniques. The majority of sophisticated methods use global thresholds for every pixel, however adaptive thresholding is more flexible and can take into account changes in the image's lighting. By creating altered versions of the images, data augmentation increases the amount of the training dataset. vital for enhancing the performance of the model with small sample sizes. lowers the danger of overfitting and increases framework correctness.

Alzheimer's disease (AD) is a chronic brain ailment that is incurable, but there are treatments that can slow its course. In order to control and prevent AD, early detection is essential. This has led to the development of an end-to-end framework for medical picture categorization in different phases of AD utilizing convolutional neural networks (CNN). Using 2D and 3D brain scans from the ADNI dataset, the approach uses straightforward CNN architectures and transfer learning with a pre-trained VGG19 model. A online tool for remote AD checking is developed in response to the COVID-19 pandemic, which helps physicians and patients identify AD stages and provide pertinent guidance. Evaluation measures show that the CNN architectures are effective; for 2D and 3D multi-class AD stage classifications, they obtain promising accuracies of 93.61% and 95.17%, respectively, whereas the VGG19 model achieves 97% accuracy. This method tackles overfitting, memory needs, and computing complexity, which makes it a workable option for remote AD assessment[5].

We conduct a thorough analysis of Alzheimer's disease (AD) staging by integrating different data modalities, namely, single nucleotide polymorphisms (SNPs) for genetic information, clinical test data, and magnetic resonance imaging (MRI), using deep learning (DL) algorithms. Three-dimensional convolutional neural networks (CNNs) handle image data, while stacked denoising auto-encoders extract features from genetic and clinical data. A novel approach to data interpretation that uses perturbation analysis and grouping finds the best features that the deep models have learned. Based on the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, our findings show that deep models perform better than shallow models like decision trees and support vector machines. Moreover, the incorporation of multimodality data outperforms single modality models with respect to mean F1 scores, accuracy, precision, and recall. The Rey Auditory Verbal Learning Test (RAVLT) and the hippocampal and amygdala brain regions were identified as distinctive traits, which are consistent with the body of research on AD that has already been published[6].

In this work, a convolutional neural network (CNN) that integrates multi-modality data from T1-MR and FDG-PET images of the hippocampus region is presented for the diagnosis of Alzheimer's disease (AD). This method, which uses 3D image-processing CNNs to learn diagnostic features for AD, does away with the requirement for manually retrieved features, in contrast to typical machine learning techniques. The ADNI dataset included 731 cognitively unimpaired participants (CN), 647 AD subjects, 441 subjects with stable mild cognitive impairment (sMCI), and 326 subjects with progressive mild cognitive impairment (pMCI). The classifier was trained on paired T1-MR and FDG-PET images from this dataset. The suggested network demonstrated state-of-the-art performance with excellent accuracies of 90.10% for CN vs. AD, 87.46% for CN vs. pMCI, and 76.90% for sMCI vs. pMCI tasks. Notably, the outcomes highlight that using CNNs for classification does not need segmentation, and that combining imaging data from two different modalities improves overall performance[7].

The goal of this research was to establish a computer-aided diagnostic (CAD) system for early detection of Alzheimer's disease (AD) patients and AD-related brain regions by developing a unique classification approach combining eigen brain and machine learning. The idea was to provide an aiding tool, not to take the role of clinicians. The paper's contributions consist of five main areas: The objectives of this study are as follows: (i) extending the Eigen brain to MR images and validating its efficacy; (ii) suggesting a hybrid eigen brain-based CAD system that can identify AD in subjects who are normal control (NC) as well as brain regions associated with AD; (iii) proving that the method's classification accuracy is on par with state-of-the-art techniques, with identified brain regions correlating with published research; (iv) utilizing inter-class variance (ICV) and Welch's t-test (WTT) to eliminate redundant data; (v) emphasizing the POL kernel's superiority over linear and RBF kernels for this study[8].

This paper presents the current initiative, which aims to build and implement a medical system to improve the quality of life for individuals with Alzheimer's disease and reduce the burden on their caregivers. A Smart Biomedical Aid is an electronic device that provides an automated medication reminder system, a call button in case of an emergency during the day, a map showing the patient's location, and round-the-clock stable status monitoring for Alzheimer's patients. The two components of the gadget are worn by the patient, and the second serves as an internet of things (IoT) platform application for the caregiver. The global position sensor module (GPS), heart rate sensor, processing unit sensor, wearable unit, and LCD display with microcontrollers were all implemented using motion. This unit is supported by a (IoT) platform, which allows the caregiver to interact with the patient from any place. Two elements are used in the proposed system design: a wearable device worn by the patient and a platform application installed on the caregiver's smartphone. The wearable unit was composed of four parts: the control unit, display unit, power unit, and sensor unit. The accelerometer and gyroscope sensors that make up the sensing unit are designed to give information on the wearable device's stability as well as the patient's health in order to identify falls, which are common in individuals with Alzheimer's disease. The sensors continuously determine the location and tilting angles by measuring the angular velocity and acceleration about the three axes. [9].

In this study, we discuss the development, implementation, and first testing of an artificial intelligence-powered voice assistant that will provide caregivers with customized guidance and recommendations around food, nutrition, and cooking for a family member with ADRD. This voice assistant provides the ADRD caregiver with continuous access to valuable guidance on food, nutrition, and eating habits. Meals and snacks are also suggested. Each patient's situation is different, and the recommendations and guidance are customized based on their preferences, health conditions, and ADRD stage. The assistant's recommendations are also influenced by the caregiver's financial status, educational background, and time limits. Since voice is the most common mode of communication, a voice assistant provides a natural way to connect with technology that doesn't require any kind of training. More than one-third of caregivers are older adults, thus this is especially beneficial for them[10]. They may find it difficult to use other forms of technology that require fine motor skills, good vision, or hand-eye coordination.

One of the primary problems that Alzheimer's patients face, especially when they are alone and away from home, is not being able to navigate their way around. The goal of the Adriano-based positioning and healthcare system covered in this paper is to help caregivers and patients with Alzheimer's disease track and monitor remote vital sign monitoring. The case study and the system's output show how the system may assume this responsibility and help Alzheimer's patients in a number of ways. The created system can track the patient's location and keep an eye on their vital signs, such as their temperature and heart rate. Additionally, the device has the ability to save these data on a micro SD card and send the information to caregivers every five minutes. The patient's vital signs are obtained using a temperature and heart rate sensor, and the microcontroller receives the data for processing[11].

Encouraging people with mild (early-stage) and moderate (middle-stage) Alzheimer's disease to maintain their independence and social interactions is the aim of this work. We propose a smartphone app that uses facial recognition and position detection from Google Maps. The application aims to improve users' ability to perform daily tasks and to enhance ordinary communication by integrating a notification feature. With its ability to track whereabouts and keep Alzheimer's patients from becoming lost, its location detection feature helps keep patients secure. The application has consistently assisted persons with Alzheimer's symptoms and significantly enhanced their quality of life, according to the results. Thus, our work highlights the significance of utilizing artificial intelligence (AI)-based features, including facial recognition, in healthcare applications that could have a significant impact on the population. The proposed application has the potential to benefit all mild-to-moderate Alzheimer's patients and their caregivers by incorporating features like machine learning-based facial recognition. This helps individuals with Alzheimer's remember people in their local environment and provides them with a wearable GPS monitoring device that makes it easier for caretakers to find them[12].

Reference	Year	Name	Accuracy
1	2016	Diagnosis of Alzheimer diseases in early step using SVM (support vector machine)	90.66%
2	2018	Multimodal and multiscale deep neural networks for the early diagnosis of Alzheimer’s disease using structural MR and FDG-PET images	86.4%
3	2021	Alzheimer’s dementia recognition using acoustic, lexical, disfluency and speech pause features. robust to noisy inputs	84%
4	2021	A CNN based framework for classification of Alzheimer’s disease	97.5%
5	2021	Deep learning approach for early detection of Alzheimer’s disease	90.66%
6	2021	Multimodal deep learning models for early detection of Alzheimer’s disease stage	NA
7	2019	Diagnosis of Alzheimer’s disease via multi-modality 3D convolutional neural network	NA
8	2015	Detection of Alzheimer’s disease by three-dimensional displacement field estimation in structural magnetic resonance imaging	92.57%

9	2020	A smart biomedical assisted system for Alzheimer patients	NA
10	2020	A personalized voice-based diet assistant for caregivers of Alzheimer disease and related dementias: System development and validation	NA
11	2020	Design and development of Arduino healthcare tracker system for Alzheimer patients	NA
12	2020	Alzheimer assistant: A mobile application using machine learning	NA

3. PROPOSED SYSTEM

The Smart Secure IOT Assistant-Based System for Alzheimer's disease is revolutionized by the integration of intelligent machine learning, IoT, image processing and Embedded C programming. This proposed system combines the of machine learning algorithms such as Local binary Pattern Histogram algorithm and Haar Cascade Classifier for face detection and reorganization. A key component in guaranteeing the smooth integration and management of these smart devices is Embedded C, a programming language frequently used for embedded systems.

The convergence of embedded C programming, intelligent machine learning, IoT, and image processing revolutionizes the Secure IOT Assistant-Based System for Alzheimer's Disease. For face detection and reorganization, this suggested method integrates machine learning algorithms like the Haar cascade classifier and the local binary pattern histogram algorithm. The smooth integration and control of these smart devices are made possible in large part by the programming language known as embedded C. In this case, we first gather pictures of the patient's friends and relatives and save these datasets in a cascade classifier. Each member may be easily identified thanks to their individual ID. To record metadata about the data that has been collected, including its source, format, date of collection, and any applicable tags or labels, create a YAML file here. Next, use the LBPH technique to train the dataset. Once a model has been trained, you may want to record details about it in a YAML file, including the model's architecture, hyperparameters, evaluation metrics, and training history. Lastly, the LBPHFaceRecognizer and cascade classifier use speech communication to identify the arriving person. Furthermore, using embedded C programming and sensor modules, an Internet of Things-based mobile application is developed to track GPS location, detect wetness, and determine whether or not the patient is panic.

In this research, developed a prototype that helps the person with AD identify their family members and assist their daily routines. The prototype is developed in the form of a cap and hip belt. Consequently, we employ a clever algorithm that, using a database as a guide, divides the identified photos into two groups: those recognized as family members and those unknown—not related to the family. The face reorganization is based on LBPH algorithm and Haar Cascade is a machine learning object detection algorithm. Consequently, people with AD can carry out their regular activities with the help of the recommended prototype. The prototype enables assistance for individuals suffering from mild to moderate AD. The prototype provides voice communication with the coming person's name when they are around family members; otherwise, it provides voice communication with the coming person's unknown identity.

Voice detection and face recognition are both possible with the prototype. As a result, the proposed prototype provides authentication support services for persons with AD.
In addition, include an IoT-based mobile application with an alert system to ensure the physical safety of the patient with AD. For that, a system for tracking the current location of Alzheimer's patients can also be used to identify whether the patient gets panicked or not by checking their heartbeat level. As a result, when they get panic, their heartbeat level gets high, and they get an alert notification through this mobile application. Using this system, family members can protect them using this tracked location details and alerts system. And moreover, there is a wetness system to identify patient excrement. When the diaphragm gets wet, family members will get a notification through the same mobile application, which will help them maintain the hygiene of the patient. As a result, in addition to providing mobility assistance and psychological support, the proposed prototype also includes measures to guarantee the physical safety of AD patients.

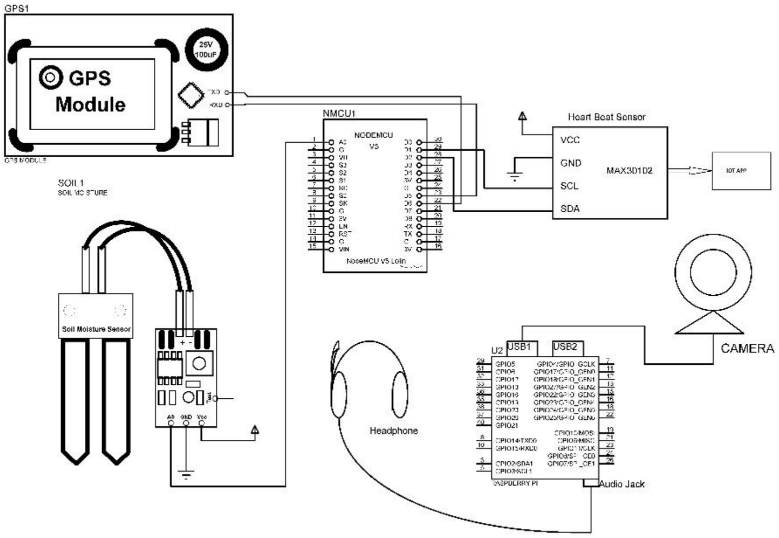

Figure 1 : Block diagram of prototype

4. METHODOLOGY

The Secure IOT Assistant-Based System for Alzheimer's disease is revolutionized by the integration of intelligent machine learning, IoT, image processing and Embedded C programming. This proposed system combines the of machine learning algorithms such as Local binary Pattern Histogram algorithm and Haar Cascade Classifier for face detection and reorganization. Embedded C, a programming language commonly used for embedded systems, plays a crucial role in ensuring the seamless integration and control of these smart devices. The convergence of embedded C programming, intelligent machine learning, IoT, and image processing revolutionizes the Secure IOT Assistant-Based System for Alzheimer's Disease. For face detection and reorganization, this suggested method integrates machine learning algorithms like the Haar cascade classifier and the local binary pattern histogram algorithm. The smooth integration and control of these smart devices are made possible in large part by the programming language known as embedded C. In this case, we first gather pictures of the patient's friends and relatives and save these datasets in a cascade classifier. Each member may be easily identified thanks to their individual ID. To record metadata about the data that has been collected, including its source, format, date of collection, and any applicable tags or labels, create a YAML file here. Next, use the LBPH technique to train the dataset. Once a model has been trained, you may want to record details about it in a YAML file, including the model's architecture, hyperparameters, evaluation metrics, and training history. Lastly, the LBPHFaceRecognizer and cascade classifier use speech communication to identify the arriving person. Furthermore, using embedded C programming and sensor modules, an Internet of Things-based mobile application is developed to track GPS location, detect wetness, and determine whether or not the patient is panic.

I. Face Recoganization

The acronym for Local Binary Patterns is LBP. It is a method for describing an image's texture or patterns. Consider examining a grayscale image pixel by pixel to comprehend LBP. We look at the neighbourhood of each pixel, which is made up of the pixel and the pixels around it. We compare a pixel's intensity value with that of its neighbours to get the LBP code for that pixel. If the intensity of a neighbouring pixel is equal to or higher than the intensity of the central pixel, we assign a value of 1, and if it is lower, we assign a value of 0. We traverse the neighbourhood in either a clockwise or counterclockwise direction, beginning at a reference pixel. We assign a 1 or 0 at each step based on the comparison between the intensity of the current neighbour and the intensity of the central pixel. After comparing each neighbour to the last one, we are left with a series of 1s and 0s. The central Pixel's LBP code is represented by this sequence. It depicts the neighbourhood's textural pattern. We create an entire LBP representation of the image by going through this process again for each pixel in the picture. The texture properties of the image can then be described and examined using this representation. Here, we identify facial features using this LBP approach.

A. Components Of Face Recognition

1. Face Detection: This is the first step where the system identifies and locates human faces in images or video frames. It involves algorithms that scan the input data for patterns resembling faces.
2. Face Alignment: After detection, the system might align the detected faces to a standard pose or orientation. This ensures consistency in subsequent processing steps.
3. Feature Extraction: Once faces are detected and aligned, the system extracts key features from them. These features could include the relative positions of facial landmarks such as eyes, nose, mouth, as well as more abstract features like texture and shape.
4. Classifier: The feature representation is then used to classify or identify the faces. This could be a simple comparison to a database of known faces or a more sophisticated machine learning model that learns to distinguish between different individuals.
5. Database Management: For recognition tasks, a database of known faces is necessary. This database needs to be efficiently managed, allowing for fast retrieval and comparison of features during recognition.
6. Matching Algorithm: This component compares the extracted features of the input face with those stored in the database to find the best match. Various matching algorithms can be used, such as Euclidean distance, cosine similarity, or neural network-based approaches.
7. Decision Making: Based on the results of the matching algorithm, the system makes a decision about the identity of the input face. This decision might include confidence scores or probabilities indicating the system's level of certainty.

II. Voice Communication Support System For Recoganization And Todolist

The voice communication technology assists the AD patient in identifying the coming person and assist them in carrying out their everyday activities. The idea behind this support system is when the coming person is a known person that is the image of the coming person is trained with specific ID and their name and also their relationship also the system say their name and also their relationship, otherwise the system say the coming person is an known person. Moreover that a time based TODOLIST support also implemented with it. When the specific time will occur the prototype started to remind the patient to do their daily activities. And this can be achieved by the built-in function in Python makes this engine.say(), and another built-in function engine.runAndWait() engine can iterate over this person's name and To Do list .

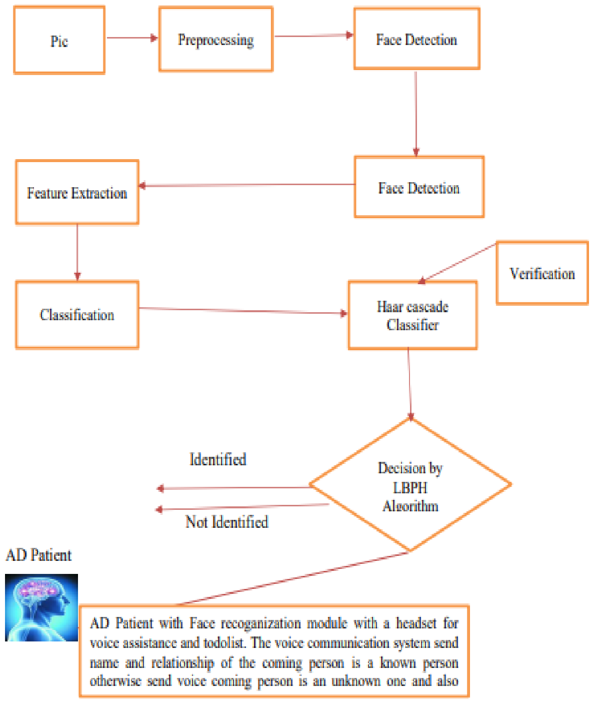

Figure 2 : Voice Communication Support System For Recoganization And Todolist

III. GPS Location Tracking System

In this proposed system, a dedicated Blynk IOT-based mobile application has incorporated which designed for family members to track the location of patients when they go out. When four or more GPS satellites are in clear sight of one another, the Global Positioning System (GPS), a space-based satellite navigation system, may deliver location and timing data in any weather condition anyplace on or near Earth. Here, the location is tracked using the NEO-6M GPS module. he NEO-6M GPS module is communicated with the node MCU microcontroller using the URT (Universal Asynchronous Receiver Transmitter) protocol because it provides effective communication between the GPS module and the IOT application and maintains reliable data transmission. The data from the GPS module is in the form of a string. From this string data, the latitude and longitude of the current location of the patient can be found, and the location details can be displayed when family members press the virtual button in the mobile application.

IV. Security System Using Heartbeat Sensor

Mild to moderately affected AD patients may lose track of where they are or may wander, possibly in search of surroundings that feel more familiar. So, in this situation, the patients get panicky and can’t get back to their house, so in this situation, their biological conditions will change, like their heart rate, blood pressure, etc. So, by sensing the heartbeat of the patient, family members can identify whether they are panicking or not by using the IOT- based mobile application. Use the digital pulse oximeter and heart rate sensor MAX30102 for this purpose. A red LED, an infrared LED, and a photodetector make up the

MAX30102 sensor, respectively. The red LED has a wavelength of 660 nm, whereas the infrared LED has a wavelength of 880 nm. The MAX30102 sensor uses a photodetector to detect the reflection after shining light through the skin. A photoplethysmogram is the term for this type of light-based pulse detecting system. The sensor can hold any body part of the patient, and when the heartbeat of the patient gets high, the value is mapped into an IR value, and the value can be displayed in the mobile application. When the patient gets panicked, an alert sound with a specified message will be triggered on their phone, and the family member can protect them using this system in association with the GPS location track system.

IV. Wetness Sensor System

The wetness sensor can be located in the diaphragm, and it contains an electrode so that when the electrode gets wet, the resistivity will decrease, which means that the diaphragm is getting wet. It also notifies through the alert sound and message through the IOT-based mobile application, which helps to change the diaphragm immediately by the family member or caretakers. The working principle behind this is that when the electrode gets wet, conduction will occur, and a threshold value is set to notify the diaphragm whether it is wet or dry. When the diaphragm is dry, the controller-taken threshold value is greater than 800 (the maximum value is 1024), and when the diaphragm is wet, the controller-taken threshold value is less than 800.

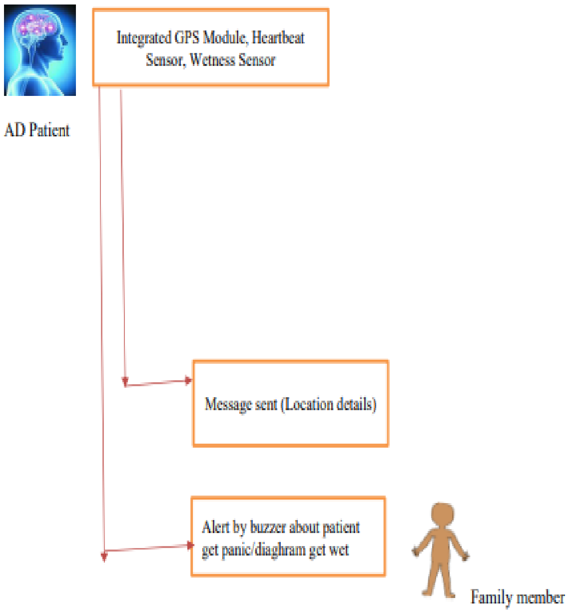

Figure 3: Location Tracking. Wetness sensor and security system

5. HARDWARE AND SOFTWARE IMPLEMENTATION

Implementation of software with hardware in the AD assistance are possible by using Blynk IoT and efficient algorithms. Fundamentally, it involves choosing the right hardware, like cameras, embedded systems, and sensors, each of which is picked based on how well it can support the software's computing demands while enabling smooth communication over Internet of Things protocols. These sensors and cameras are strategically positioned to capture images of their family members, track the location of patients when they go out, security alert based on sensors and also to detect the wetness related to the patients execration. Following the establishment of the hardware infrastructure, attention turns to software development.

Use the Raspberry Pi 3, which has 4 GB of RAM, for the voice and facial recognition systems. It is a single-board computer with sufficient power given its compact size. Here, the recorded data is analysed using the Haar cascade machine learning algorithm and LBPH face recognition algorithms. This involves model training to accurately classify the images into two categories, such as known persons and unknown persons, a task that demands careful preprocessing and feature extraction to ensure optimal performance. For facial recognition on the Raspberry Pi3, the entry is an image from a webcam. First, OpenCV, which is a library of opensource computer vision and machine learning software is executed for determining whether there is one or more faces in the image. If the faces are found, we identify their coordinates and conditionally cut out only that part of the general frame, transfer it for recognition and match it with the available images in the database. We have installed the OpenCV package which allows us to also develop facial recognition and object recognition systems/ Mainly, our python implementation is based on dlib library that is appropriate for solutions based on machine learning and image processing. And the camera can be located at the USB port of this Raspberry Pi 3 module. For voice assistance, use a wired headphone, and attached to this same module is an audio jack port.

Here, patients' locations were tracked using the NEO 6MV2 GPS module and NODE MCU V3 microcontrollers. It receives the signals sent out by satellites and uses universal asynchronous receiver-transmitter (UART) communication to continually transfer information when given a direct voltage of 3.3 V. The GPS module and controller can transmit data securely and efficiently thanks to the UART protocol. The UART protocol works in asynchronous mode, so each time it provides 8-bit data in the form of longitude and latitude into the Blynk IoT application through the transmit and receive pin of the GPS module. And the last 3 digits of this longitude and latitude will change when the patient’s location is in a specific geographical area. The transmit and receive occur with the help of the software serial header file. While using this serial header file, you can choose any pin in the microcontroller for transmit and receive instead of the controller’s receiver and transmitter pin, and here the transmitter and receiver are connected to the D6 and D5 pins of the microcontroller. So using this good practice helps reduce the issues related to the time of code flashing to the microcontroller and may cause improper communication between the Blynk IoT application.

The system for patient security is put into place. An electronic gadget called the MAX30102 heart rate sensor measures the difference in oxygen-rich and oxygen-less blood to determine an individual's heart rate. This sensor, which was created by Analog Devices, can detect pulse oximetry (SpO2) and heart rate (HR) information. It has two LEDs—one red and one infrared—a photodetector, optics, and a low-noise signal processing unit.The main idea is to shine a single LED at a time and check the amount of light that is getting reflected back to the sensor. Based on the reflection, it determines the blood oxygen level and heart rate. The pulse oximeter and heart rate sensor's VCC pin, which can be linked to either the 3.3V or 5V power source, is the power supply pin.SCL stands for Serial Clock. The master device pulses this pin at a regular interval to generate a clock signal for communication. Connect to the D1 pin of the controller. SDA stands for serial data; through this pin, data exchange happens between two devices. Connect this pin to the D2 pin of the microcontroller. The pins SCL and SDA are utilized by the sensor to communicate with microcontrollers. A red LED, an infrared LED, and a photodetector make up the MAX30102 sensor, respectively. The MAX30102 sensor shines both the light through the skin and measures the reflection with the photodetector. A photoplethysmogram is the term for this type of light-based pulse detecting system.The oxygen in the hemoglobin has a specific characteristic: it can absorb IR light. When the concentration of hemoglobin is higher, the blood is redder. Which simply means it can absorb more IR light. As the blood is pumped through the veins in the finger, the amount of reflected light changes, creating an oscillating waveform. And by measuring this wave, we can get the heartbeat reading. When the IR value exceeds a specific range, get a buzzer alert to the IoT-based mobile application, and the family can identify that patient, panic, and protect them. And these are implemented use of embedded C programming language.

The wetness sensor system is implemented using an FC-28 moisture sensor. The idea behind this proposal is that when the electrode gets wet, conduction will occur, and a threshold value is set to notify the diaphragm whether it is wet or dry. When the diaphragm is dry, the controller-taken threshold value is greater than 800 (the maximum value is 1024), and when the diaphragm is dry, the controller-taken threshold value is less than 800. Additionally, this module has a potentiometer that will set the threshold value; the comparator (LM393) can assess the value. Depending on the threshold value, the LED will either turn on or off. The A0 pin of this sensor is connected to the microcontroller's A0 pin for data transfer.

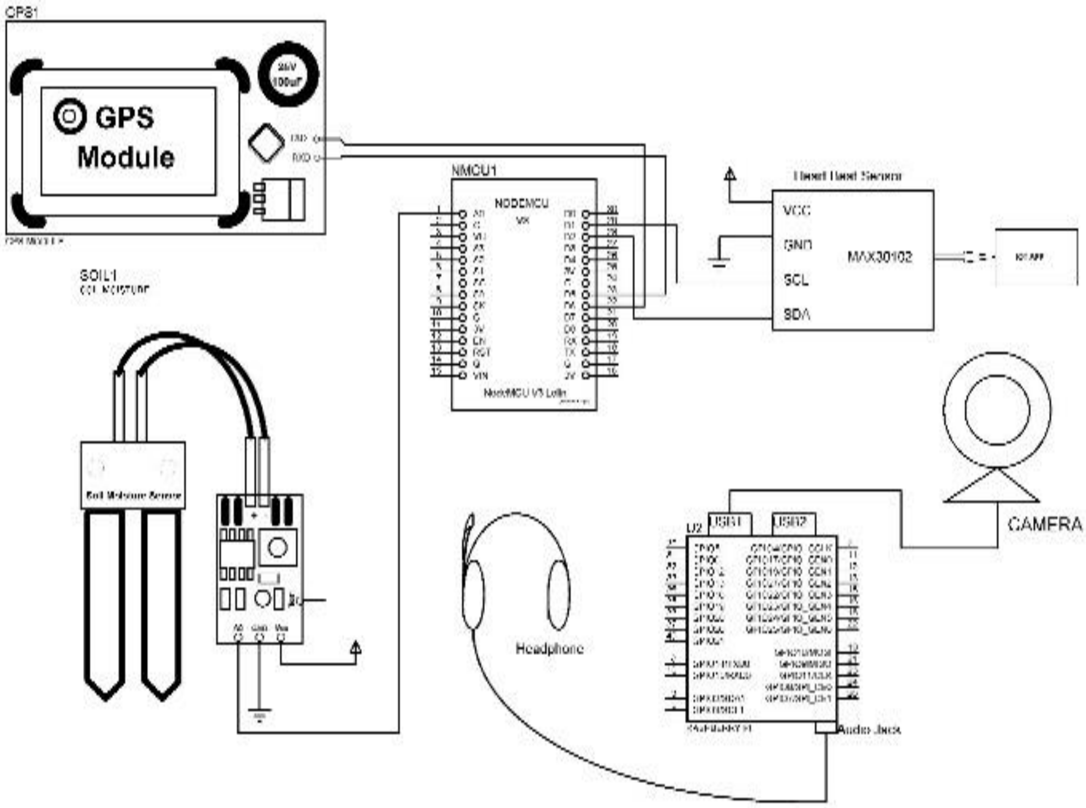

Figure 3. Circuit Diagram

6. HARDWARE COMPONENTS AND SPECIFICATIONS

1.Raspberry Pi and Camera Modules

In this prototype, the Raspberry Pi and camera module are crucial components. Because face recognition is the research's most alluring feature, these modules cover this section in its entirety. The camera module connects to the Raspberry Pi module's USB connection in order to gather datasets, which is the first stage of image processing. The trained model is loaded into the Raspberry Pi module, which effectively and accurately recognizes faces in collected images by classifying them using the pre-trained model.

Figure 4: (i)Raspberry Pi (ii)Web Camera

2.GPS Module

One of the most significant features of this prototype is the ability to track a person's location, which helps to ensure the patient's safety when they leave their home. A GPS receiver uses the time it receives signals from high-altitude GPS satellites to determine its position; it then uses the transit time of each message to calculate the distance to each satellite using the speed of light. The GPS module antenna tracks the location and displays the latitude and longitude when a family member clicks the virtual button in the IoT-based mobile application.

Figure 5: GPS modules NEO-6M

3. Node MCU

An essential component of this prototype is the Node MCU. The Node MCU enables smooth communication between different hardware modules and sensors. In order to ensure the security of the patient, it gathers information from sensors like heartbeat, moisture, and GPS modules. After that, this information is sent to the Blynk IoT application, which is used by family members or caretakers. Additionally, a number of secure data transmission protocols, including UART and URT, are used to handle data transfer.

Figure 6 Node MCU Development Board/kit v0.9

4. Heartbeat Sensor

The ability of these sensors to sense heart rate is crucial for guaranteeing the patient's safety in this prototype. The very versatile MAX30102 sensor detects blood oxygen saturation, heart rate, and body temperature. This sensor was developed by Analog Devices and can detect heart rate (HR) and pulse oximetry (SpO2). It contains optics, a low-noise signal processing unit, a photodetector, and two LEDs—one red and one infrared. The fundamental idea is to switch on one LED at a time and gauge the amount of light that is reflected to the sensor. When the IoT program detects an IR value greater than a threshold, it computes the heart rate and helps determine whether the patient is in a panic or not.

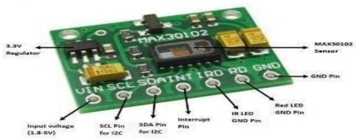

Figure 7 MAX30102 Digital Pulse Oximeter and HeartRate Sensor

5. Wetness Sensor

The patient's hygiene is maintained by this sensor. There are four pins on the FC-28 moisture sensor. This module has a potentiometer to set the threshold value, and the comparator, LM393, can determine the value. The threshold value will determine whether the LED turns on or off. When conduction occurs in the electrode, the threshold value changes; a high value indicates that the diaphragm is dry, and a low value suggests that it is moist.

Figure 8 Wetness sensor

Sensor / Module	Specifications
Camera Module	Camera
GPS Module	NEO 6MV2
Node MCU	ESP8266
Heartbeat Sensor	MAX30102
Wetness sensor	FC-28 moisture sensor
Raspberry Pi	4 GB of RAM
Headphone	Samsung

Table 1. Model of sensor and modules

7. IMPLEMENTATION AND RESULTS

The prototype design and its outcomes are depicted in the figure. Here, a headset is attached to allow the patient to receive voice communication aid, and a hat is integrated with a Raspberry Pi module for face recognition. The face recognition module is powered by a power bank module. The hardware modules and sensors for position tracking, wetness sensing, and security systems are fastened to a patient-friendly hip belt. Additionally, an IoT-based mobile application with a tracking location and security alarm buzzer is incorporated. The family member can manage this application and safeguard the patient.

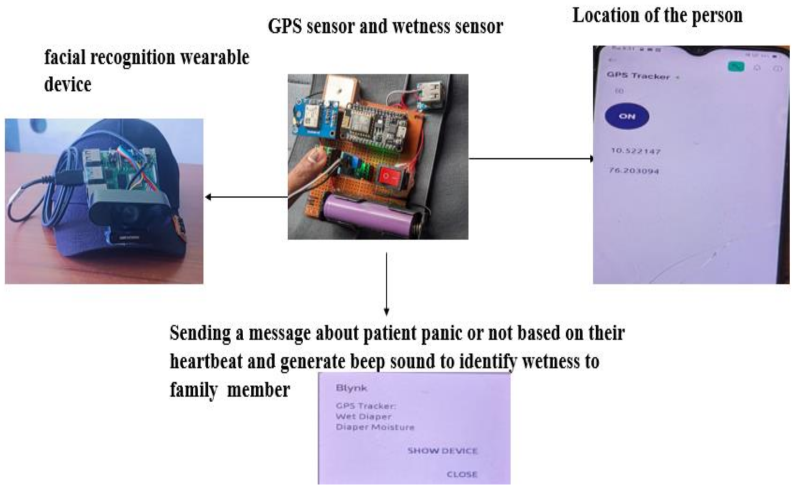

Figure 9 Prototype design

International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

A. FACIAL RECOGNITION AND TODO LIST RESULTS

The core idea of the assistance system is based on the use of the LBPH and Haar cascade algorithm. The wearable device captures the image and each image are associated with a unique ID so it avoids duplication. Once detect the image it gives good identification not only a single person but also multiple person can be identify by using the prototype. More over that the prototype assist to do the daily activities of patient based on a time based TODO LIST and the result is given below.

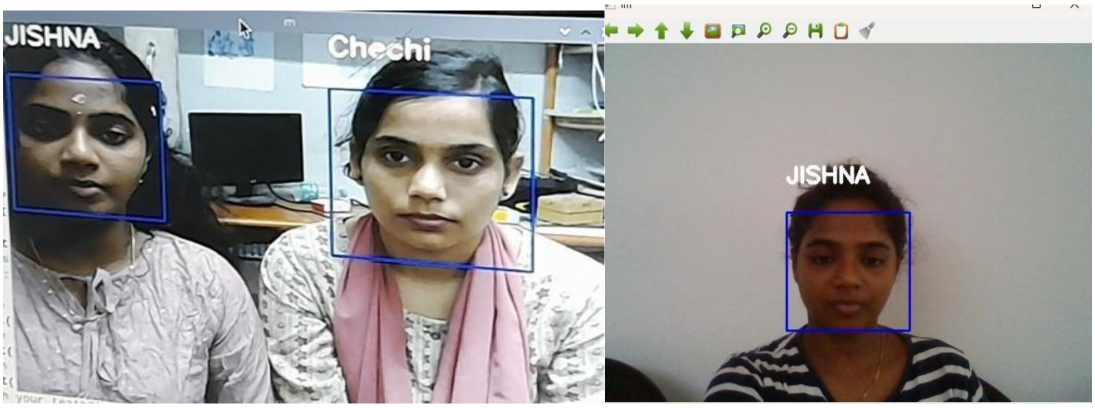

Figure 10 Face Reorganization

Figure 11 TodoList

B. GPS LOCATION TRACKING, WETNESS SENSOR SYSTEM AND SECURITY SYSTEM RESULTS

The location details such as longitude and latitude are sent to the Blynk IoT application when the family member press the virtual button in the IoT application. And also, when the patient get panic they can't identify their location or can't be reach to their home the heartbeat rate get exceed above the threshold IR value at that time alert buzzer sound will triggered and also give the message through mail. So using these detail the family member can be protect patient using this prototype. Similarly when the wetness sensor detect the wetness of diaphragm the buzzer sound and message also sent to the application.

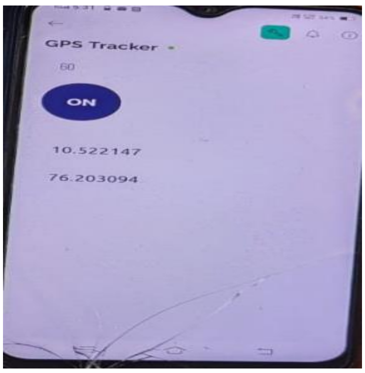

Figure 12: Location Tracking(Longitude and Latitude are shown in the figure)

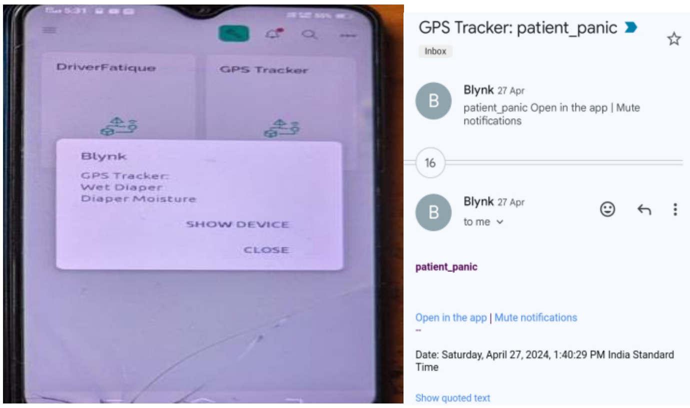

Figure 11 Security alert and Wetness alert

8. CONCLUSION AND FUTURE WORK

The creation of a Secure IOT assistant-based system for Alzheimer's disease has shown promising results in utilizing machine learning, image processing, and IoT, hence facilitating effective care for patients suffering from mild to moderate AD. By utilizing machine learning models and Internet of Things sensors, the system is able to provide patients with support. The prototype helps patients manage their daily schedules and rearranging their families with voice assistance. The ability to identify family members, provide voice communication, and assist with their daily tasks are demonstrated by machine learning-based image processing algorithms that were trained on image datasets.

Suggest developing a face recognition cap so that the person with AD will be glad to wear the prototype. Taking this into consideration, use an ingenious algorithm that splits the recognized images into two categories based on a specified database. The prototype uses many methods to obtain noteworthy outcomes. The goal of this project is to create a prototype that offers psychological support services and guarantees secure data transmission, allowing a family member to look into and safeguard the AD patient. Even if there are numerous AD solutions, there aren't many systems that rely on AD help. Additionally, facial recognition and security features continue to be a difficult issue for the systems that are now in place to assist in enhancing the quality of life for people with AD. The idea put out in this study is to create a straightforward aid for those with AD.

In the future, building on our research, we propose using a high-resolution camera to recognize people and objects more accurately. We also plan to replace the Raspberry Pi module with a high-speed microcontroller to expedite recognition and supply long-term power for the entire hardware setup. To make the prototype easier to transport, make it smaller.

REFERENCES

1. B. Rabeh, F. Benzarti, and H. Amiri, ‘‘Diagnosis of Alzheimer diseases in early step using SVM (support vector machine),’’ in Proc. 13th Int. onf. Comput. Graph. Imag. Vis. (CGiV), Beni Mellal, Moroco, Mar. 2016, pp. 364– 367.
2. D. Lu, K. Popuri, G. W. Ding, R. Balachandar, and M. F. Beg, ‘‘Multimodaland multiscale deep neural networks for the early diagnosis of Alzheimer’s disease using structural MR and FDG-PET images’’ Sci. Rep., vol. 8, no. 1, pp. 1–13, Dec. 2018

3. M. Rohanian, J. Hough, and M. Purver, ‘‘Alzheimer’s dementia recognition using acoustic, lexical, disfluency and speech pause features robust to noisy inputs,’’ in Proc. Interspeech, Shanghai, China, Aug. 2021, pp. 3220–3824.
4. Y. Abdulazeem, W. M. Bahgat, and M. Badawy, ‘‘A CNN based frameworkfor classification of Alzheimer’s disease,’’ Neural Comput. Appl., vol. 33, no. 16, pp. 10415–10428, Aug. 2021.
5. H. A. Helaly, M. Badawy, and A. Y. Haikal, ‘‘Deep learning approach forearly detection of Alzheimer’s disease,’’ Cogn. Comput., vol. 21, pp. 1–17, Nov. 2021
6. J. Venugopalan, L. Tong, H. R. Hassanzadeh, and M. D. Wang, ‘‘Multimodal deep learning models for early detection of Alzheimer’s disease stage,’’ Sci. Rep., vol. 11, no. 1, pp. 1–13, Dec. 2021.
7. Y. Huang, J. Xu, Y. Zhou, T. Tong, and X. Zhuang, ‘‘Diagnosis of Alzheimer’s disease via multi-modality 3D convolutional neural network,’’ Frontiers Neurosci., vol. 13, pp. 1–12, May 2019
8. S. Wang, Y. Zhang, G. Liu, P. Phillips, and T.-F. Yuan, ‘‘Detection ofAlzheimer’s disease by three-dimensional displacement field estimation in structural magnetic resonance imaging,’’ J. Alzheimer’s Disease, vol. 50, no. 1, pp. 233–248, Dec. 2015.
9. Q. A. Ahmed and A. Q. H. Al-Neami, ‘‘A smart biomedical assisted system for Alzheimer patients,’’ in Proc. 3rd Int. Conf. Sustain. Eng. Techn., Bristol, U.K., 2020, pp. 1–20.
10. J. Li, B. Maharjan, B. Xie, and C. Tao, ‘‘A personalized voice-based diet assistant for caregivers of Alzheimer disease and related dementias: System development and validation,’’ J. Med. Internet Res., vol. 22, no. 9, pp. 1–11, 2020.
11. O. T. Esfahani and J. Moshayedi, ‘‘Design and development of Arduino healthcare tracke system for Alzheimer patients,’’ Int. J. Innov. Technol. Exploring Eng., vol. 5, no. 4, pp. 12– 16, 2015
12. N. Aljojo, R. Alotaibi, B. Alharbi, A. Alshutayri, A. T. Jamal, A. Banjar, M. Khayyat, A. Zainol, A. Al-Roqy, R. Al-Magrabi, T. Khalawi,andS. Al-Harthi, ‘‘Alzheimer assistant: A mobile application using machine learning,’’ Romanian J. Inf. Technol. Autom. Control, vol. 30, no. 4, pp. 7–26, Dec. 2020