Dijlah Journal of Engineering Science (DJES) Vol. 2, No. 4, December, 2025, pp. 77-87
ISSN: Printed: **3078-9656, Online: 3078-9664**, paper ID: 81

Jasmine : An Application of AI- Assistance in Healthcare Supporting

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Article Info

Article history:

Received Aug., 27, 2025
Revised Sept., 30, 2025
Accepted Nov. 10, 2025

Keywords:

Artificial Intelligence (AI)
Healthcare Applications
Voice Assistance (VAs)
Deep Learning (DL)
YOLO

ABSTRACT

AI-driven decision support systems and voice-assisted health monitoring are becoming revolutionary technologies in contemporary healthcare applications. They also show promise as ways to improve accessibility for elderly and disabled patients and support healthcare systems. Even still, current approaches frequently do not combine deep learning, speech, and vision into a single framework. Voice-powered AI systems aim to automate these processes, allowing physicians to dedicate more time to direct patient care. This shift not only improves healthcare delivery but also boosts provider well-being. From a patient perspective, voice assistants increase accessibility and engagement, especially for elderly and disabled populations. These systems enable patients to manage appointments, receive medication reminders, and access health information without navigating complex interfaces. This research addresses this gap by developing a multimodal AI-powered assistant capable of interacting with users through voice commands, real-time image analysis to provide timely medical information.

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1. INTRODUCTION

As people age, their health and psychological stability often decline, making them more vulnerable to chronic illnesses such as diabetes, hypertension, arthritis, and memory-related conditions like Alzheimer’s. In addition to these medical issues, neglect by family members and lack of emotional support can further deteriorate their well-being. Therefore, elderly individuals require proper healthcare, assistance, and support to help them cope with daily challenges and maintain their quality of life. Digital voice technologies have led the transformation of the health sector and show promise to contribute to solving major challenges facing healthcare systems worldwide, including providing personalized medicine, preventing chronic diseases, caring for the growing elderly, and providing healthcare to hard-to-reach populations. Intelligent digital platforms with a conversational user interface (i.e., conversational agents) are a representative technology that has been investigated in these contexts. Conversational agents simulate human interaction by using natural language processing to analyze user input and respond appropriately using human language via auditory or textual modalities[1]. This research explores the integration of Artificial Intelligence (AI) techniques particularly voice interaction, image recognition, and Deep Learning[2] to develop a virtual healthcare assistant. The system is designed to support patients, especially the elderly and disabled, by offering real-time medication recognition . This application will be a very useful tool for patients, offering two main advantages: ease of access and use, and the availability of relevant information. Based on deep learning technology, users will be able to capture an image of their medication in real time and the application will provide them with appropriate instructions. This will significantly contribute to the development of healthcare services in the near future.The assistant uses technologies such as Google’s Speech Recognition API [3] and Text-to-Speech (gTTS) [4]for interpreting and responding to user voice commands, YOLO object detection models [5]for identifying medicines from images captured by a webcam, Deep learning models for analyzing and interpreting data accurately. The system achieved a 90.4% accuracy in real-time medicine recognition and showed reliable integration between voice and vision components. The aim is to simplify access to medical instructions, enhance patient independence, and reduce the burden on healthcare professionals. The study concludes that while the system is promising, further work is needed to refine AI integration and improve its adaptability and accuracy in diverse real-world settings.

2. Related Works

Many researchers have made remarkable efforts to predict voice assistance in individuals over different periods. This part offers an overview of the research on the achievements to date

2.1.Voice assistant for Diagnosing Diseases

In 2024, Alper et al. [6] presented a study to investigate the use of machine learning techniques to classify Chronic Obstructive Pulmonary Disease (COPD) based on voice analysis factor. The study was based on a Systematic Literature Review (SLR) to assess existing research on machine learning applications for voice-affecting disorders and identified gaps in COPD classification. A new Swedish COPD voice classification dataset was created, and three ML algorithms were tested on voice recordings, focusing on vowel "A" sounds collected via a mobile application. While the study had focused on the potential of ML-based voice analysis as a decision support tool for COPD detection, the challenges were dataset size constraints and the need for broader validation in diverse populations. **In 2024, Summoogum et al.** [7] used voice-based system for detecting Diabetes Type 2 using a conversational virtual assistant in a home environment. The study had used acoustic ML techniques to extract and analyze seven non-identifiable features from recordings of 24 person included older adults interacting with a virtual assistant. The system is distinguished by its prediction accuracy of 60% for females and 70% for males. This demonstrated the feasibility of integrating voice-based pathology analysis. While the research offered a promising, non-invasive, and accessible pre-screening tool for early diabetes detection, limitations were the small dataset size and the need for improved accuracy across diverse populations.

2.2. Voice Assistant for Supporting Medical Practice

In 2021, Kim et al. [8] developed a Smart Hospital Assistant (SHA) that works with a system that combines a voice assistant with artificial intelligence to improve surgical outcomes. A virtual assistant was presented as an assistant capable of simulation and voice interaction with the ability to recognize natural language in addition to its design for the purpose of performing routine non-surgical tasks in the operating department. The advantages and prominent points were that it helped in time reducing, improving staff resources, and reducing direct contact between patients and the staff, thus reducing the risk of transmission and infection of germs and microbes at the surgical site. Despite the development of technology that aims to improve efficiency and safety and address the point of staff shortage in some health facilities, the challenges included the need to ensure accurate training of users and also verification and readiness to deal with different scenarios and cases in reality. **In 2023, Kumah-Crystal et al.** [9] provided a voice assistant for health records Vanderbilt Electronic Health Record Voice Assistant (VEVA). This assistant was designed to support and facilitate clinical work based on voice navigation between electronic health records and was developed as a website that quickly responds to voice commands and performs the required tasks. It was tested by 14 users at the medical center with positive reviews of its functions in recording and summarizing health data and 64% of users expressed satisfaction with using the system in its current state. The study highlighted possibilities for modification such as improving the process of responding to speech and summarizing more detailed records. The study showed that with develop the system, the system can contribute significantly to the usability of electronic records and user efficiency.

2.3. Voice Assistance for Elders Support

In 2022, Chen et al. [10] conducted a study on Intelligent Voice Assistants (IVAs) to enhance healthcare services and support Quality of Life (QQL) in the elderly. This study did not focus on machine learning applications or specific data, instead, it focused on user experience and empirical analysis. The test was conducted by interviewing 5 healthcare providers and 16 elderly people. It was then found that there are about 12 barriers that the elderly face in their daily lives and routine tasks. Some challenges were found in developing this type of voice assistant to meet the needs of the elderly, as well as the possibility of improving these systems to provide better service to help the elderly. Table 2.1 summarizing the main different points between the studies above.

Table2.1.Comparison of Previous Works

Study	**Year**	**Used Techniques**	**Dataset**	**Main Findings**	**Advantages**	**Challenges\Limitations**
Alper et al. [6]	2024	Systematic Literature Review (SLR), Machine Learning (ML), Vowel "A" Focus	New Swedish COPD voice dataset	Focused on COPD detection using voice analysis and machine learning techniques	Potential decision support tool for COPD detection	Small dataset, need for broader validation
Kelvin Summoogum et al. [7]	2024	Acoustic Machine Learning, Voice Feature Extraction, Virtual Assistant Interaction	24 older adults' voice recordings	Developed a triage system for detecting Type 2 Diabetes using voice patterns.	Feasible, non-invasive early detection tool, can be used in home environments with limited resources	Small sample size, need for accuracy improvement across diverse populations.
Kim et al. [8]	2021	AI-powered voice assistant (SHA) for surgery	Simulated surgeries	SHA reduced operating time, optimized staff resources, and minimized infection risks.	Improved efficiency, reduced infection risks, optimized staff use.	Requires user training, needs real-world validation.
Kumah-Crystal et al. [9]	2023	VEVA voice assistant for EHR navigation	Tested by 14 users at a medical center	64% user satisfaction, improved voice-based EHR interaction.	Enhances usability of electronic records, increases efficiency.	Needs improved response accuracy and record summarization.
Chen et al. [10]	2022	User interviews to identify barriers and opportunities for improving intelligent virtual assistants (IVAs).	Interviews with 16 older adults and 5 healthcare providers.	Identified 12 barriers in IVA design for older adults; focused on user-centric design and empirical analysis.	Enhances understanding of older adults' challenges and opportunities for improvement.	Does not include specific data analysis or machine learning applications.
Yang et al. [11]	2023	Large language models (LLMs) for natural language understanding and summarization in Talk2Care system.	Tested with 10 elderly users and 9 healthcare workers.	Improves communication and data collection; reduces effort for healthcare providers.	LLM-powered summarization; user-friendly dashboard; enhances communication.	Privacy, ethical considerations, and scalability issues.

. **In 2023, Yang et al.** [11] introduced Talk2Care LLM (large language models) based on voice assistant designed to support and enhance communication between the elderly and healthcare workers. The system relied on natural language understanding and summarization of language models (LLMs) to collect health information. The system featured a voice assistant interface for easy interaction for the elderly, while for healthcare workers it provided an LLM-powered dashboard to review previously summarized data. The system was tested by 10 elderly users and 9 healthcare workers. The results showed that Talk2Care helps improve communication, enhances data collection, and reduces the effort required by healthcare providers, but there are certain challenges such as privacy and ethical considerations, in addition to the scalability of the system. This study done using LLMs, which are a type of deep learning model known for their powerful natural language processing and summarization capabilities. Each study mentioned above has its own advantages and disadvantages, depending on different assumptions, which raises several issues that need to be addressed.

3. METHOD

The goal was providing an interactive system that would contribute to healthcare. Voice technologies, real-time image recognition and interaction to enable patients and users to interact with the medical system easily and accurately. In summary, the methodology of this system based on deep learning algorithms. organized into the following stages; The first stage is data collection, which involved capturing real images using a PC camera or webcam, in addition to obtaining images from the internet for different types of medications with various uses. The second stage is the design of an interactive system with the patient, by employing different techniques of image processing, image analysis, speech recognition, text-to-speech conversation technique in python language with using different libraries . The third stage included the use of the YOLO model to detect and train the system then integrating it with the Wolfram Alpha platform[12] to provide users with the necessary information about the medication. Finally, the system evaluation stage was conducted by applying performance metrics after integrating the techniques and algorithms into a unified system, ensuring reliability, efficiency and accuracy in performing the required tasks. All stages are shown bellow in Figure 3.1.

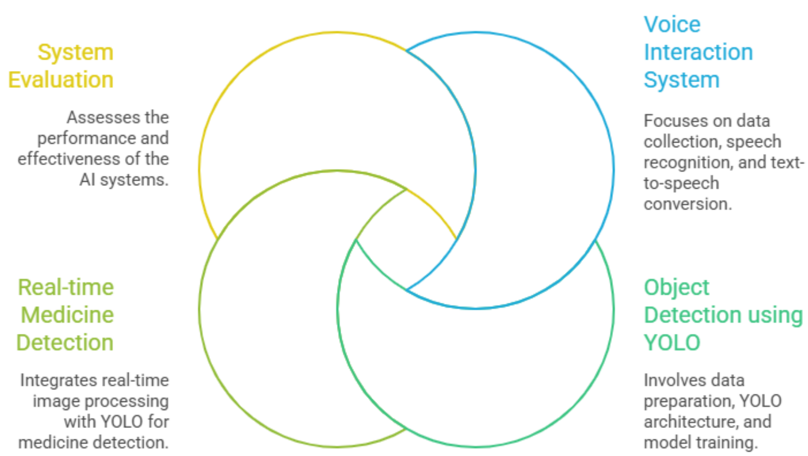


Figure 3.1. An Over View of Proposed System

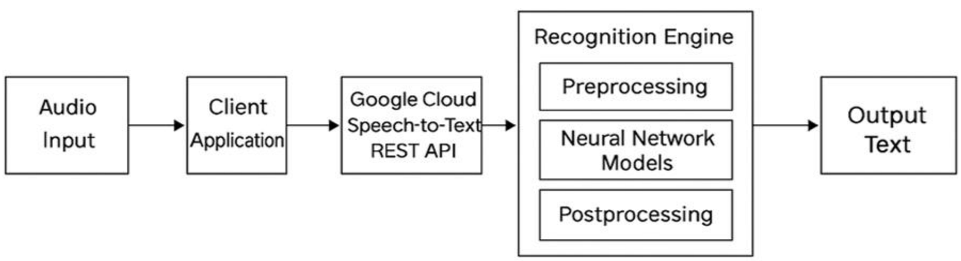
3.1. Data Collection

As mentioned above, this stage referred to the process of collecting data and images, both from real-world sources and the internet, for different types of medications. Approximately 40 images were captured and collected for each medication separately, considering the variations among the manufacturing companies. These images were labeled and divided into sets for training, testing, and validation, prepared and partitioned into 70 % for training, 20 % for testing, and 10 % for validation. Figure 3.2 Showing some of dataset that used in the system.

3.2.Dataset images of The Proposed System

3.2. Voice Interaction system

The voice assistant, named "Jasmine," was developed using Python[13], relying on pre-built audio processing libraries: the Speech Recognition library for speech-to-text recognition, the TTS library for converting text to speech using Google's Speech Engine, and the PlaySound library for playing the resulting audio file. Speech Recognition was used based on Google API, The API supports over 125 languages. The gTTS library was used to convert text to speech. enabling the care robot to respond with speech that Relying on TTS to reproduce information audibly. WaveNet [14] relies primarily on extended causal convolution, a deep learning model for generating raw audio It can produce a human voice to make inanimate robots behave more human-like. Figure 3.3 a block diagram of Google Speech Recognition API.



3.3.The Block diagram of Google Speech Recognition API

3.3. Object Detection Using YOLO

Though several models were used, the most important one was the YOLO model (YOU ONLY LOOK ONCE) , an AI model capable of immediately identifying objects in images and movies. YOLOv10[15] , was used in this work to exactly detect medicines. The algorithm of YOLO model is shown in Figure 3.4(a) and confusion matrix of YOLO model training is shown in figure 3.4(b).

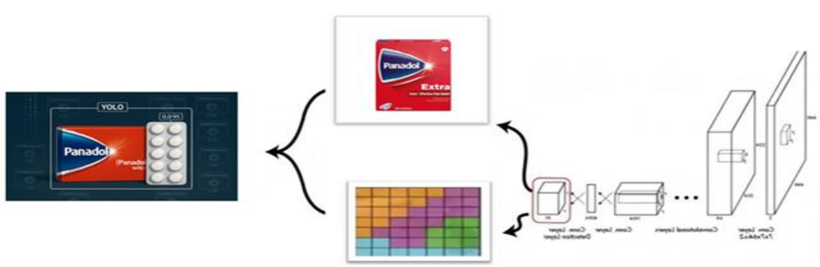


Figure 3.4 (a) YOLO Algorithm

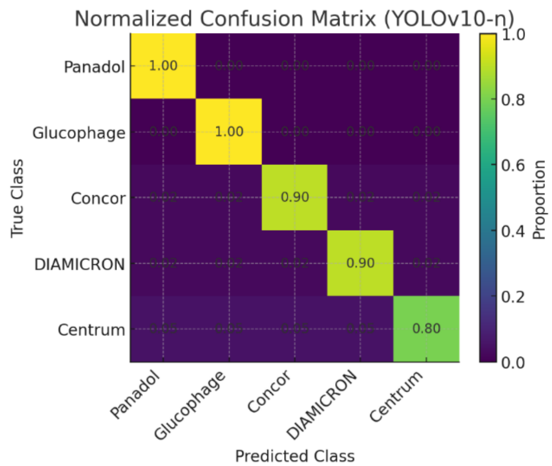


Figure 3.4 (b) Confusion Matrix of YOLO Model Training

3.4. Performance Evaluations Metrics

performance metrics such as Accuracy, Recall, Precision, IoU, F1-score, WER, mAP@0.5[16]. They were essential for evaluating the effectiveness and accuracy of the developed interactive system. They help analyze the efficiency of models used in speech ,medicine detection and the quality of integration between different systems.

3.5. System Structure

The system is built using three main hardware components: a microphone for capturing user voice, a high-resolution webcam for visual data input[17], and a Dell Inspiron 3593 laptop with Intel i7 CPU and 16GB RAM to process tasks efficiently. On the software side, Python serves as the main programming language, integrating various libraries and frameworks. Ultralytics YOLO is employed for medicine detection, while OpenCV handles image and video processing. SpeechRecognition and gTTS enable speech-to-text and text-to-speech functionality for the voice assistant. Supporting libraries such as numpy, os, threading, and tempfile ensure smooth operation and data handling. Additionally, the Wolfram API provides a powerful knowledge layer for advanced computations, analytics, and query responses.

Overall, the system combines audio, vision, and AI modules into a unified multimodal health-monitoring platform that enables real-time medicine recognition and gesture-controlled voice interaction. Figure 3.5 is showing the block diagram of the system and Figure 3.6 showing the mechanism of the system work.

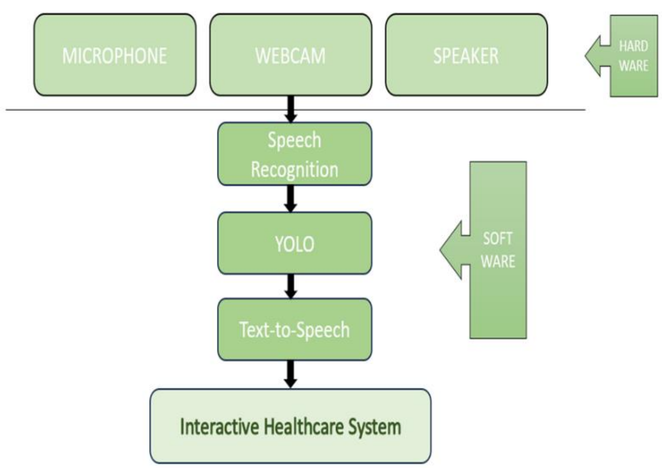


Figure 3.5. Block Diagram of Used Software and Hardware

Figure 3.6 Mechanism of The system

4. RESULTS AND DISCUSSION

The system was tested in all its components to evaluate its performance from several aspects. The following is an explanation of the most important aspects evaluated:

4.1. Speed and Response Time

- Google's speech recognition API , takes approximately (1-2 sec) to return text after the user has finished speaking[18].
- Executing commands such as opening the camera or taking a photo is almost instantaneous (0.5 sec).
- Analyzing the image using the YOLO model on the CPU took approximately (0.5-1 sec), as mentioned above, which is considered relatively good.
- Converting text to speech via TTS and downloading the audio file from the internet took approximately (1-2 additional seconds). Table 4.1 showing the time response.

Stage	Average of Time Response
Speech Recognition	≈1.5 sec
Command Execution	≈0.5 sec
YOLO Reasoning	≈0.75 sec
Text to Speech	≈1.5 sec

Table 4.1. Time Response

4.2. Quantitave Results

The table 4.2 below summarizing some quantitative performance indicators after training and testing.

Table 4.2. Quantitative Performance Indicators Results after Training

Indicator	**Precision**	**Recall**	**F1-Score**	**mAP@0.5**
Value (%)	95.35	92.0%	93.3%	90.4%

4.3. Accuracy and Validity of Results

The YOLO medicine detection module's accuracy was quantified during training and testing, achieving an 90.4% , as noted. This demonstrates a high ability to detect legitimate packs and tablets.

4.4. Real-Time Results of Medicine Detection

- Real-time Image Processing: Covering image enhancement and OpenCv frame extraction detects medication in real time.
- YOLO Integration: Integrate the model by analysing the model when the real camera has been connected with it.

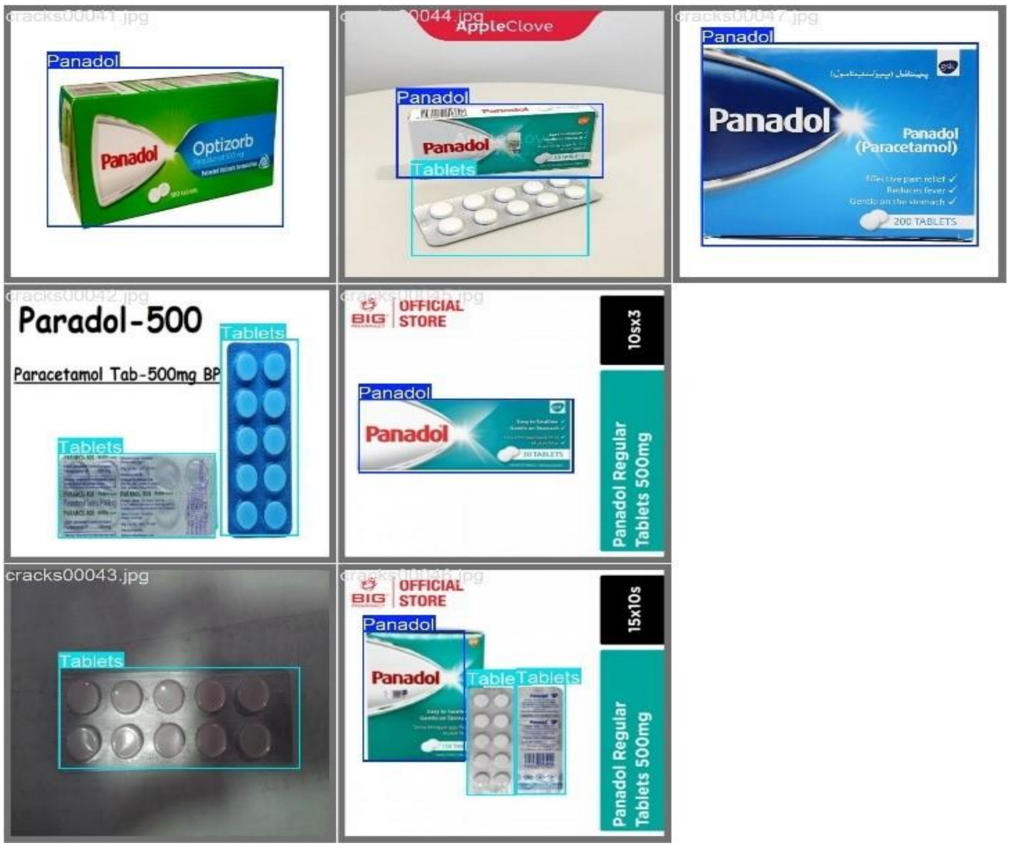


Figure 4.1. Real-time Detection for Medication Based on YOLO Model

4.5. Performance Metrics

Table 4.3 of the most important performance metrics for the five medicine classes on which the model was initially trained.

Table 4.1. Performance Metrics of Medication Classes

Class	**Precision %**	**Recall%**	**F1-Score%**	**mAP @0.5**
Panadol	99.5	100	99.8	99.5
Glucophage	98.1	100	99.0	98.1
Concor	93.3	90.0	91.6	91.6
DIAMICRON	92.3	90.0	91.3	91.6
Centrum	87.2	80.0	83.4	70.3

4.6. Comparison with Previous Studies

Table 4.4 contrasts the proposed system against six recent healthcare voice-assistant frameworks focusing on medicine information retrieval. Our model ranks highest in multimodal support and achieves competitive accuracy at markedly lower latency due to the efficient YOLOv10 backboned facilitates rapid debugging for researchers.

4.4. Comparison with Previous Studies

Study / System	**Modality**	**Dataset size**	**Accuracy / mAP**	**Avg. end-to-end latency**	**Notable strengths**	**Key limitations**
This work (YOLO-v10 + voice)	Vision + Voice	1 200 medicine & gesture images	mAP 0.89, Precision 95.35 %	This work (YOLO-v10 + voice)	Vision + Voice	1 200 medicine & gesture images
DocPal [19]	Voice only	500 hrs of transcripts	Word-error 7 %	n/a (cloud)	Hands-free EHR updates	HIPAA integration still manual
VEVA [20]	Voice only	14 clinicians, 120 notes	Task success 92 %	< 2 s	EHR navigation shortcuts	Limited to Vanderbilt system
Talk2Care [21]	Voice + LLM	10 patients	F-score 0.83	cloud-only	Summarises long-term logs	Privacy & cost
Smart-Hospital Assistant [22]	Voice	3 simulated ORs	Task time ↓ 18 %	real-time	Infection-control benefit	Needs staff training
VIPA ward trial [23]	Voice	746 bedside units	84 % interactions non-clinical	< 1 s	Off-loads TV/info requests	Little clinical impact

5. CONCLUSION

In conclusion, this work aims to enhance the interaction between the user and the voice assistant, ensuring easy access to medical instructions and guidelines related to treatment. This supports patient comfort and also helps save time and effort for healthcare providers. The system shows promising results, but it still requires further work to validate the proposed integration of deep learning-based data processing. This will help build a smarter, more accurate assistant system, ultimately making it a valuable practical tool for users to obtain health assistance more smoothly. The system achieves 90.4% accuracy. The system as a whole has proven successful in integrating several modern technologies to achieve a natural interface for users with cognitive abilities. The system is fast enough for interactive use on a CPU alone, and accurate in performing its basic tasks, including reading text, understanding speech, and recognizing medications. The system is considered relatively integrated because it provides a seamless experience between audio and video.

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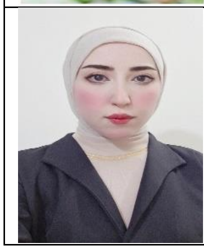	B.Sc. in Medical Instrumentation Techniques Engineering – Al-Isra'a University,Bachdad , Iraq (2021) M.Sc. Student in Medical Engineering Technology (Electronics) - Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq