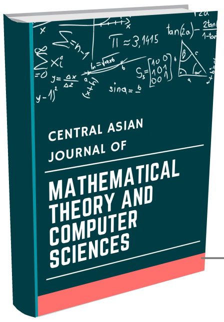

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Artificial Intelligence in Covid-19 Diagnosis

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Abstract:

The Coronavirus has quickly spread to more than 200 nations, infecting several million people globally in a matter of weeks. Artificial intelligence (AI) tools have been shown to be beneficial in testing, diagnosing, and efficiently limiting viral propagation. However, several flaws or limitations have been discovered in existing AI approaches. Patients are diagnosed after the onset of symptoms, making it difficult to determine the appropriate patient management. Doctors' involvement is required, which may result in viral infection via direct contact with patients. The present project attempts to create AI approaches to address such issues. This work suggests AI capable of estimating the timing of viral infection in patients and the degree of medical treatment required prior to the development of COVID-19 symptoms. Many vital biological and human functions are measured by the proposed device, including the state of the brain and neurotransmitters, mental/mood conditions, tension level of face muscles, hands, and body temperature, rate of pulse and pressure, oxygen level in the blood, rate of breathing and difficulty, degree of redness of eye(s), and general body imbalances. This work makes use of both hardware and software designs. To explore, test, and evaluate the integration/work of each subsystem component and the overall system architecture, an experimental research is used. The findings demonstrated that the suggested approach might be utilised to differentiate between healthy and infected persons prior to the manifestation of COVID-19 symptoms.

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1. INTRODUCTION

According to the World Health Organization, the coronavirus is one of the most common infections, with the virus having infected more than 200 nations and infecting more than 81 million individuals so far. Many countries and health organisations are frantically attempting to halt the spread of the new coronavirus illness pneumonia (COVID-19). Artificial intelligence (AI) tools have been proved to be one of the most efficient strategies for monitoring the spread of the virus, identifying patients, clearing regions, and speeding up the process of developing an effective vaccine, among other things that may help eliminate this pandemic.

Covid-19, a relatively new illness, is caused by a virus. In December 2019, it appeared for the first time in the city of Wuhan, China [1–4]. Huang et al. [5] used COVID-19 to describe the clinical features of 41 patients in January 2020. As a result, AI is thought to aid in the regulation of COVID-19. Researchers reached the following conclusion:

- One of the most significant factors that has assisted China in controlling the spread of the virus in record speed is the employment of AI. The backdrop of the disease's identification and confirmation by AI is based on monitoring the spread of infectious illnesses throughout the globe. This kind of finding alerted authorities to the presence of a cluster of odd pneumonia cases that happened at a market in Wuhan, China. AI also analysed worldwide airline ticket data to anticipate the course and time of subsequent travel for the afflicted population. As a result, AI proved to be a strong tool for COVID-19 prediction [6,7].
- AI may be used with image analysis techniques to give one of the instruments for coronavirus detection, quantification, AI, and monitoring [8]. Digital image processing tools have been deemed promising for coronavirus detection [9,10]. In addition to the remarkable capability of non-linear modelling, medical image processing using general neural networks was used in the diagnosis and computation of the infection potential of COVID-19 [11–14]. Shan et al. [15] used a chest CT image to construct a deep learning-based system for autonomous segmentation of lungs and infection locations. Using lung CT scans and deep learning methods, Xu et al. [16] tested a screening model for discriminating between influenza and COVID-19 for viral pneumonia. Wang et al. [17] created a deep learning approach based on COVID-19 graphical characteristics to offer a clinical diagnosis prior to pathogenic testing. COVID-19 contains distinct radiological fingerprints and picture patterns, as shown by Hamimi et al. [18]. Szegedy et al. [19] investigated neural networks to discriminate between COVID-19-infected and non-infected individuals. The dataset showcases 259 patients utilising thousands of photos to demonstrate the COVID-19 model. Similarly, Zhou et al. [20] and Chen et al. [21] used neural networks to introduce the diagnostic attitude of various persons (healthy and sick) utilising between 5000 and 6000 photos.

COVID-19. Wang [22] suggested COVID net, a deep conventional neural network, for detecting COVID19 patients from chest X-ray pictures with 83.5 percent accuracy. Deep learning algorithms on CT scans were utilised by Wang et al. [23] to screen COVID19 patients with 89 percent accuracy. Joaquin [24] described a validation approach with 96.2 percent accuracy using a small dataset of 339 photos for training and evaluating deep learning techniques. The research offered a methodology for classifying COVID19 and standard Xray pictures. Yan et al. [25] developed a prediction algorithm to detect high-risk individuals before they progressed from moderate to serious symptoms. Santosh [26] concentrated on the development of new paradigms based on AI-driven technologies, using a mix of machine learning algorithms and data modalities. Al-Qaness [27] updated the adaptive neuro-fuzzy inference system technique, which is based on an improved flower pollination algorithm and the slap swarm algorithm. Computational paralinguistic analysis is used to analyse speech/sound [28]. Rao and Vazquez [29] suggested utilising a cell phone to identify COVID-19 patients. The problems in sound/speech technique, on the other hand, include automatic identification of coughing, breathing difficulties, and sneezing. The preliminary review highlights several ways for diagnosing COVID19. However, the disadvantages of such procedures include patient diagnosis only after symptoms appear, which leads to viral transmission and poor control conditions. Furthermore, none of the approaches can assess the essential patient care without a doctor's participation through mandatory checks, increasing the load on physicians as well as the possibility of viral infection due to direct contact with the patients. By upgrading existing AI methodologies, our effort intends to give a solution to such difficulties. This study is part of our research in many issues and engineering problem resolution, which you can see in the early research [30-76].

2. DIAGNOSIS OF COVID-19

COVID-19 is a new virus that attacks the pulmonary alveoli. In critical health situations, the infection may cause lung damage and serious respiratory failure. To prevent severe or catastrophic instances, infected people should be diagnosed, isolated, and treated as soon as feasible. Patients with COVID-19 may be divided into four categories according on their health status: (a) mild cases, in which symptoms are mild and no pneumonia manifestations are found in the lungs; (b) moderate cases, in which symptoms such as fever and respiratory tract symptoms, as well as pneumonia manifestations, can be seen in lung images; and (c) severe cases, in which the respiratory rate is greater than 30 breaths per minute and oxygen saturation is less than 93 percent at rest; additionally, the arterial partial pressure of oxygen (PaO2) is less than 300 mmHg with (case C). Critical instances are further subdivided into three categories: (d1) early stage, (d2) medium stage, and (d3) late stage.

3. DESIGN ALGORITHMS

To read physiological indications and electrical bio-signals, several sensors are used. The signals are then transferred to a microcontroller that has been programmed with an artificial fuzzy algorithm to correlate the gathered data with human health and make the appropriate judgments (e.g., recommendations based on human health state and level of medical care). The flowchart in Figure 1(a) depicts the working concept, and the block diagram in Figure 1(b) (b).

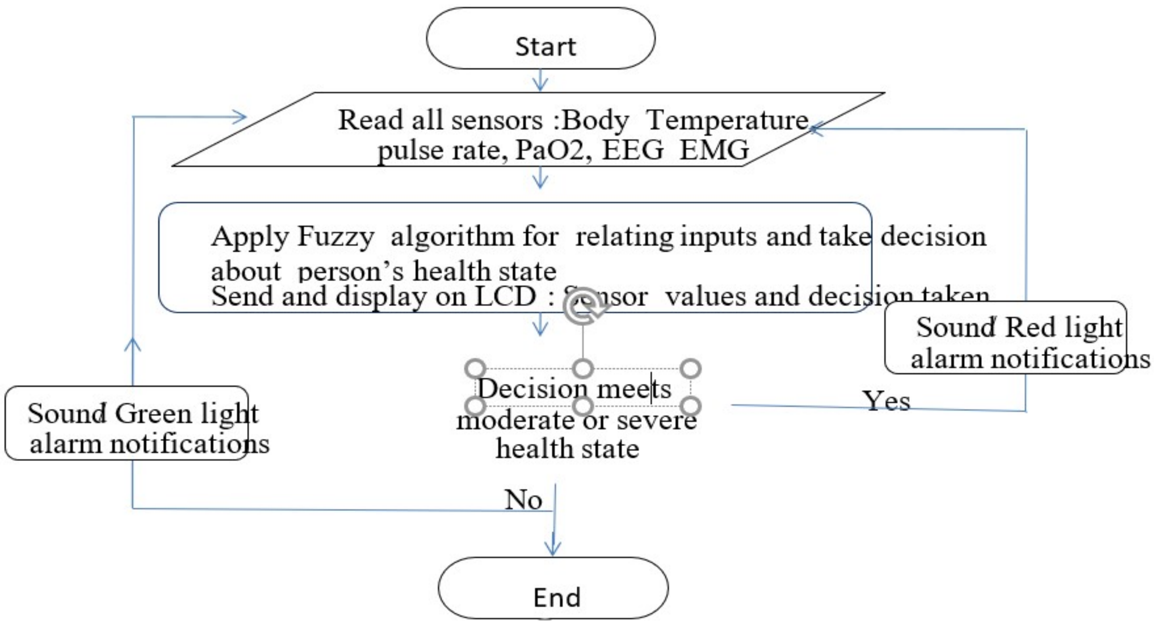

Figure 1(a) Flowchart working concept in COVID-19

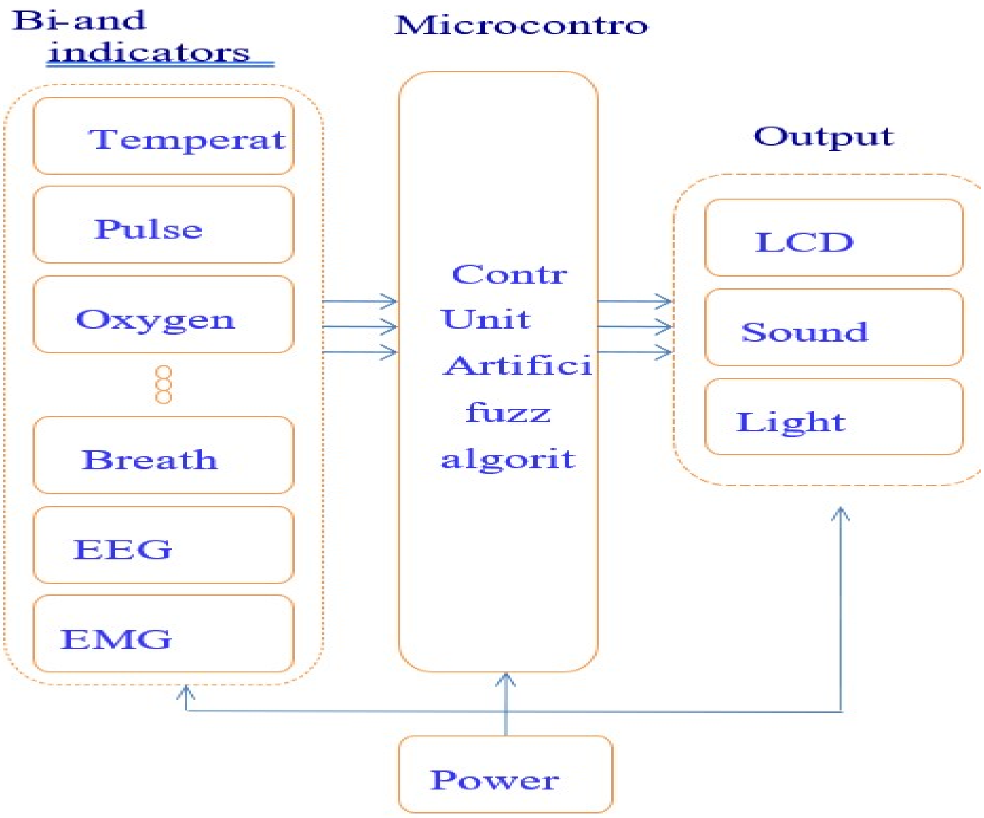

Figure 1(b) Block Diagram Of Covid-19 Treatment

4. SYSTEM CONFIGURATION AND HARDWARE DESIGN

To read bio signals and physiological indicators, several system structure and configuration options might be offered. As illustrated in Figure 2, one possibility is to construct the system as a wearable device on top of the human head with sensors located on the head and temple sides. Another design option is to split the system into two linked parts: one worn around the hand wrist and the other on the temple side of the head. The following hardware components are needed to physically design the proposed system. Sensors, physical control units, interfaces, communications, and power supplies of various types are used. Synergistic integration using embedded system design approach is employed in the system design and construction stages. The hardware components are chosen to be modest in size (up to 5 VDC operating voltage) and to have output signals that are compatible with the microcontroller spanning from 0 VDC to 5 VDC. The hardware required to read EEG and EMG bio signals is chosen using ready-made signal processing units.

Various sensors are used to assess biosignals and physiological markers in people, such as body temperature, oxygen saturation level, and heart rate. Additionally, human electrical bio-signals including signals received from muscle EMG and brain EEG are employed. For monitoring human body temperature, the DS18B20 temperature waterproof sensor with a simple one-wire interface depicted in Figure 3(a) is used. As illustrated in Figure 3, an optical heart rate sensor capable of reading heartbeats is used (b). Figure 3(c) depicts a maxim integrated MAX30102 high-sensitivity pulse oximeter used to measure the quantity of oxygen saturation level (SpO2) in the blood. The heart rate sensor is used to monitor heart rate and SpO2.

The EMG and EEG signals are selected to be in the microvolt range (often between 1 V and 100 mV). Because these signals are very weak with noise, they must be read, processed, and handled effectively, taking amplification, filtering, and illustration into account. There are many ways for reading and processing the produced human brain electrical EEG bio-signal. However, the most appropriate, simple, and straightforward method is to alter the light-weight MindFlex headset, as illustrated in Figure 3. (d). Then, as illustrated in Figure 3, an EEG signal processing circuit is used (e). Electrical EMG impulse impulses, on the other hand, are used to read and analyse the signals produced by muscle fibres. As illustrated in Figure 3, a compact (suited for wearable design) MyoWare module (AT-04-001) with a surface EMG sensor/electrode is used (f).

Figure 4 depicts the output components required for system development, which include an LCD for data exhibition, soft light (red/green), and a sound notification alert (a). Figure 4(b) depicts the bioindicator values and associated medical treatment required, which are considered based on human health status (either positive or negative outcomes) to represent the choice made by the artificial fuzzy algorithm. The choice demonstrates the necessity for intensive treatment and/or resuscitation using a 4 20 LCD character module. Figure 4 depicts the drive circuit design for connecting and controlling the microcontroller's two alarms (c). The circuit is designed using a 4.7-ohm z pulldown resistor, a PN222 transistor, and a 330 Ohms resistor for LED protection. Figure 5 shows an Arduino Nano board with a suitable microcontroller-based control unit based on an ATmega328p microcontroller (a). Figure 5 shows a suitable power supply of a rechargeable lithiumpolymer battery type with 3.7 V and 180 mAH (b). Finally, to obtain the required power level, batteries in parallel and series connections/combinations are used.

5. SYSTEM PROTOTYPING AND DESIGN

Figures 6(a) and 6(b) illustrate the entire block diagram as well as a visual depiction of the overall system hardware design and integration (b). All chosen sensors for reading physiological indications, namely body temperature, pulse rate, and breathing rate/oxygen level, are connected to the microcontroller's analogue and digital ports. Furthermore, the two related modules are linked to the microcontroller-based control unit in order to read human electrical bio-signals such as EEG and EMG. The artificial fuzzy control algorithm (made to read physiological indicators and bio-signals) turns signals into precise ranges of medical practise that can be interpreted and compared to the human health status. These ranges are used to create the input and output membership functions, which are then discussed in fuzzy logic algorithms along with additional processing values, interpretation, and decision making.

Figure 2 suggested structure for the system with sensors placement

Figure 3(a): the DS18B20 Temperature sensor

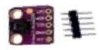

Figure 3(b): Optical heart rate sensor

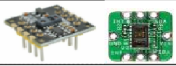

Figure 3(c): Oximeter and Heart Rate Monitor.

Figure 3(d): The mindflex headset EEG reading

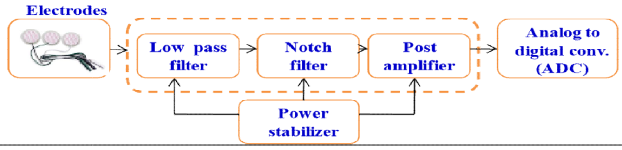

Figure 3(e): EEG signal processing circuit

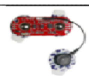

Figure 3(f): MyoWare module EMG reading

Figure 4(a): LEDs and buzzer alarm.

Figure 4(b): 4x20 LCD, characters module

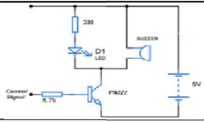

Figure 4(c): circuit diagram for interfacing alarms

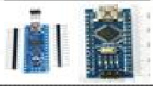

Figure 5(a): ATmega328p microcontroller-based board

Figure 5(b): Li-Po li ion, 3.7V Battery

Human bio-data and physiological indicators are used in the design to analyse health issues such as body temperature, heart rate, SPO2 level, and EMG and EEG signals. In combination with other criteria, these bio-signals and indicators serve as early detection methods for establishing the health status of any individual infected with COVID19 and recognising the need for further examination and/or treatment. Table 1 summarises the usual values of important human indicators and units.

Table 1. **Vital human signs and normal values in adults.**

Indictor	Normal value and unit
Temperature	37°C
Heart pulse Rate	60-99 bpm (beat per minute)
Oxygen saturation, SPO2	95-100%
Respiratory rate	12-16 Breaths per minutes
Blood pressure	120/80 mmHg

The DS18B20 measures human skin temperature, and this value is used to estimate human body temperature; according to standards, the rough skin temperature is about 5.1 °C lower than body temperature [78]. The DS18B20 temperature sensor is connected to the microcontroller through a 4.7 K Ohm resistor and a 5 V wire signal. To read the produced temperature signal and determine the body temperature in Celsius degrees, software integration with a manufacturer programming library is employed. Reading the human body temperature is the first step in a thorough clinical assessment. According to medical sources, this body temperature changes somewhat based on age, time of day, and exercise. The temperature of the human body is classified into distinct ranges with related meanings. Normal body temperature is defined as falling within the ranges of Temperatures range from 36.1°C to 37.5°C. A body temperature ranging from 37.7 °C to 38.3 °C often suggests hyperthermia and fever induced by a sickness or infection, whereas a temperature ranging from 38.3 °C to 40.0 °C denotes a severe fever. A body temperature of 40 °C/41.5 °C or greater implies hyperpyrexia with dinger fever and body danger. A body temperature of less than 35.0 °C, on the other hand, suggests hypothermia (low temperature). The quantity of arterial oxygen saturation in the blood, abbreviated SpO2, is a valuable measure for determining the severity of a disease. SpO2 levels are indicated for early identification of COVID-19 pneumonia, which infects human lungs and causes inflammation and pneumonia. The oxygen transport from the lungs into the circulation was harmed. Despite a typical look, a patient infected with COVID-19 has a very low oxygen level. In contrast, it is critical to establish that certain COVID-19 patients do not have low oxygen levels. Normal and healthy arterial level (SpO2 within 95 percent –100 percent), moderate hypoxemia (SpO2 within 91 percent –94 percent), hypoxic (arterial level of SpO2 is within 85 percent –94 percent), and severely hypoxic (arterial level of SpO2 is between 85 percent – 94 percent) (arterial level of SpO2 below 85 percent). A COVID-19 epidemic is typically regarded when SpO2 falls below 90%; in such a circumstance, a medical re-evaluation is strongly advised. The heart rate, also known as pulse rate, is the number of beats per minute produced by the human heart. One heart rate is distinct from blood pressure, which is the force of blood against the walls of blood vessels. COVID-19 infection is connected with changes in heart rate and pulse rate, which often increase with disease, injury, exercise, and emotions. The health of a person infected with COVID-19 is connected with an increase in heart rate; hence, the heart rate parameter aids in the detection of COVID-19 [79]. In a typical resting state, an adult's heart rate varies between 60 to 100 beats per minute. A fast heart rate (over 100 beats per minute) might be a sign of COVID-19 infection. Maxim incorporated type MAX30102 is a heart-rate sensor with a high-sensitivity pulse oximeter that measures heart rate and SpO2. Only four pins are needed in such a sensor, with SDA and SCL linked to the microcontroller analogue pins. The two signals are read and interpreted via software integration with manufacturer programming libraries. The number of breaths (inhalation and exhalation) per minute is referred to as the respiratory rate, often known as the breathing rate (bpm). When a person is infected with COVID-19, their respiratory rate increases while they experience considerable or abrupt shortness of breath and other health problems. An adult's resting respiratory rate ranges between 12 and 16 beats per minute. Values that fall outside of this range are deemed abnormal. Tachypnea means that the respiratory rate is more than 20 beats per minute. The usual respiratory rate for those over the age of 65 is between 12 and 28 beats per minute, which should be taken into account while taking sensor data.

EEG uses electrodes to read brain electrical activity from the human scalp, whereas EMG detects electrical impulses produced by muscle fibres. Muscle discomfort and relaxation may be caused by viral infection, particularly face muscles. Exercise may also cause muscle discomfort. As a result, separating pain caused by COVID-19 from pain caused by other reasons is challenging. A thorough examination reveals that the aches induced by COVID-19 are often incapacitating, acute, and last for many weeks. COVID-19-related muscular symptoms also include myalgia (tiredness and muscle pain/aches) and headache, which may be read and interpreted from EMG and EEG. In this study, EEG and EMG signals are used to identify health disorders such as myalgia, dizziness, headache, and sleeping difficulties. These findings are then used to the prediction and diagnosis of COVID-19 infection. The MindFlex headset, depicted in Figure 3(d), is a single EEG channel device used to read electrical activity in the human brain. Figure 3(f) depicts the MyoWare module EMG, a ready-made module for reading, filtering, and rectifying electrical impulses produced by muscle fibres using EMG electrodes. The output voltage of the sensor is proportional to the specified muscle activity [80]. Software integration is used for reading ranges of 0 to 5 VDC based on muscle activation. To assess the state of human health, a fuzzy algorithm model is created. As a result, based on reading human vital sign indicators and changes in their values, this model is utilised to assess the likelihood of a COVID-19 infected person(s). As input variables for the fuzzy algorithm, biosignals and physiological markers of people were used. The underlying knowledge and inference methods are intended to associate such values and make a conclusion about human COVID-19 infection using four previously described distinct scenarios: (a) mild, (b) moderate, (c) severe, and (d) critical cases. The fuzzy logic algorithm is devised and implemented using the MATLAB/Simulink method. Figure 7 depicts the development of five input membership functions employing five input bio-signals and indicators: body temperature, pulse (heart) rate, SPO2 level, EMG, and EEG; moreover, one output membership function is examined. The linguistic variables for each membership function and their accompanying ranges are constructed in accordance with predefined ranges. Table 2 summarises the interpretation and indications.

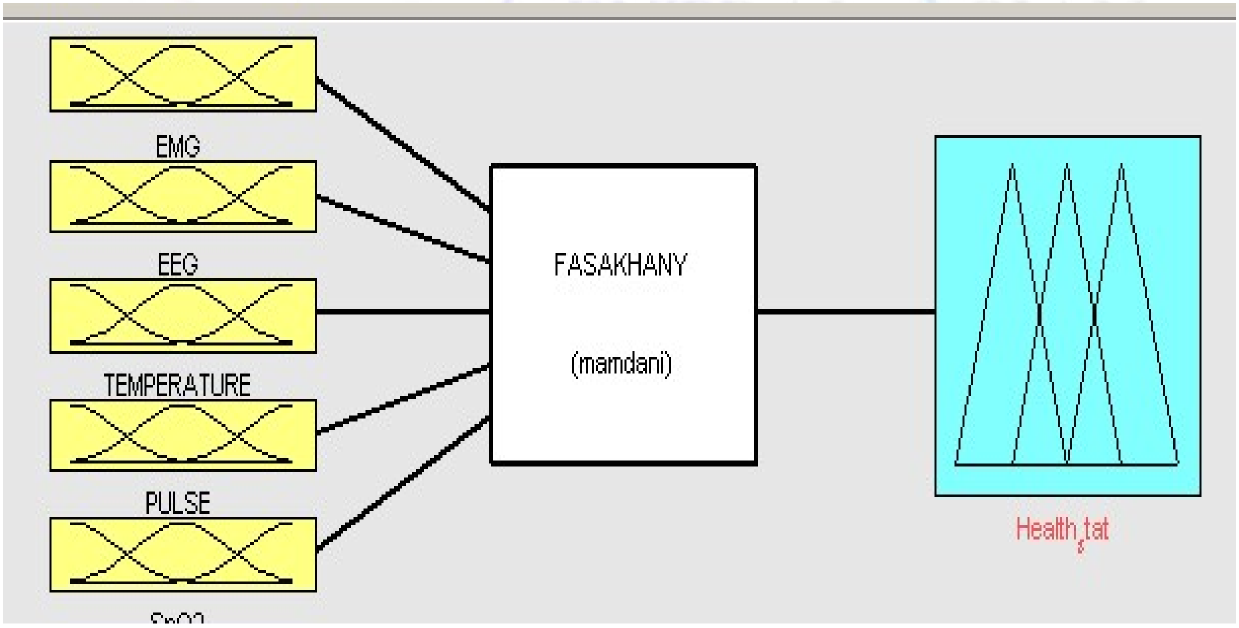

Figure 7: Development Input

Table 2. **Established ranges and interpretations for the input membership functions.**

Indicator	Ranges and indications				
Body temperature	less than (35.0 °C)	(36.1 °C) to (37.5 °C).	(37.7 °C) to (38.3 °C or infection.	(38.3 °C) to (40.0 °C)	Larger than (40.0 °C or 41.5 °C)
	Indicates hypothermia (low temperature)	Indicates normal body temperature	Indicates hyperthermia), which is fever caused by an illness or an infection	Indicates high fever	Indicates hyperpyrexia, which is fever with an extreme elevation of body temperature
SpO2 level	(95%–100%),	(91%–94%)	less than 90%	below (85%)	_
	Indicates normal and healthy arterial level	Indicates mild hypoxemia, which is below-normal blood oxygen level	Indicates low oxygen level; a medical re-evaluation is highly recommended	Considered severely hypoxic for a human	_
Heart rate	(60–90) beats per minute	(90–100)	Above (100 bpm)	_	_
	Considered normal	Indicates mild sign of infection	Could be a sign of infection and indicates serious COVID-19 symptoms	_	_

6. TESTING AND INTERNAL EVALUATION

In various situations, all subsystems, components, and hardware faults are tested. Furthermore, as discussed later, the whole system architecture is tested and confirmed. The microcontroller/Arduino with Excel communication is set up to test the functioning, reading, and software integration of each sensor in order to read data from sensors and store the results in an Excel file. Following that, such data is evaluated for a health assessment, and the results are provided. Figure 8 shows, as an example, the readings and presentation of data from all sensors for one test instance. All sensor testing data are successfully obtained, recorded, and shown numerically and graphically. Only these readings can be utilised by professionals to analyse and correlate the results; they can also describe the health status and differentiate between healthy and diseased people (s). The artificial fuzzy algorithm analyses and links the input values of each/all five bio-signals and physiological indicators using the knowledge base rule and interference mechanism; then the assessment condition and health status take place with the right conclusion about person situation in terms of COVID19 infection clinical categorization (discussed early). These examples are then utilised to describe the degree of medical treatment required, taking intensive care and/or resuscitation into account. Table 3 lists the COVID-19 categorization instances, fuzzy judgement, numerical values, medical treatment required, and colour display of the patient's state. In the present research, testing the overall system designs is achieved by merging all subsystems and components into one overall system, as illustrated in Figure 6. (b). As demonstrated in Figure 9, the hardware inloop simulation employing the input hardware sensors, Arduino board, and laptop with MATLAB/Simulink is all combined into one overall system model. Two scenarios are used to evaluate the system design and alter (raising and reducing) a specific person's bio-signals and physiological markers. The first scenario investigates physical methods for warming up and relaxing, such as pushups, running around, and meditation. The second scenario is based on a real-life example of a person who has a cold illness. The outcomes of the two cases are reviewed by taking into account the input values of bio-signals and physiological indicators, as well as the outcomes with the ultimate conclusion on medical treatment required.

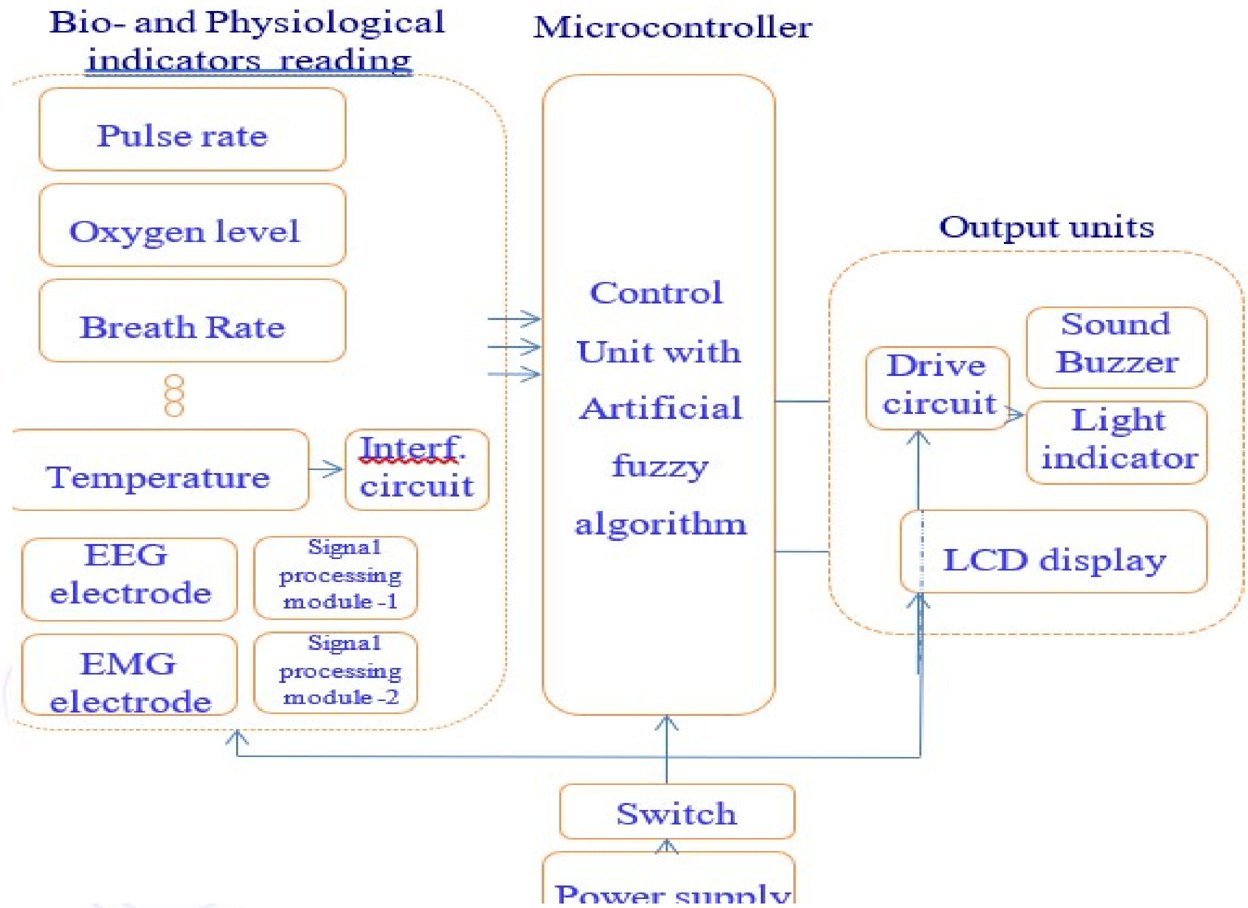

Figure 6(b) Working Design of Subsystem

Table 3. **Infection cases, fuzzy decision numerical value, and color applied.**

Fuzzy decision numerical value **COVID-19 infection state** **Health state Color** medical care needed

Between 0: 2 not infected Good Green No care needed
Between 2: 4 Mild Case Caution Red hypnosis
Between 4: 6 Moderate Case high Caution Red intensive care, (ICU) Between 6: 8 Severe Case/ Critical Cases Danger Red Resuscitation

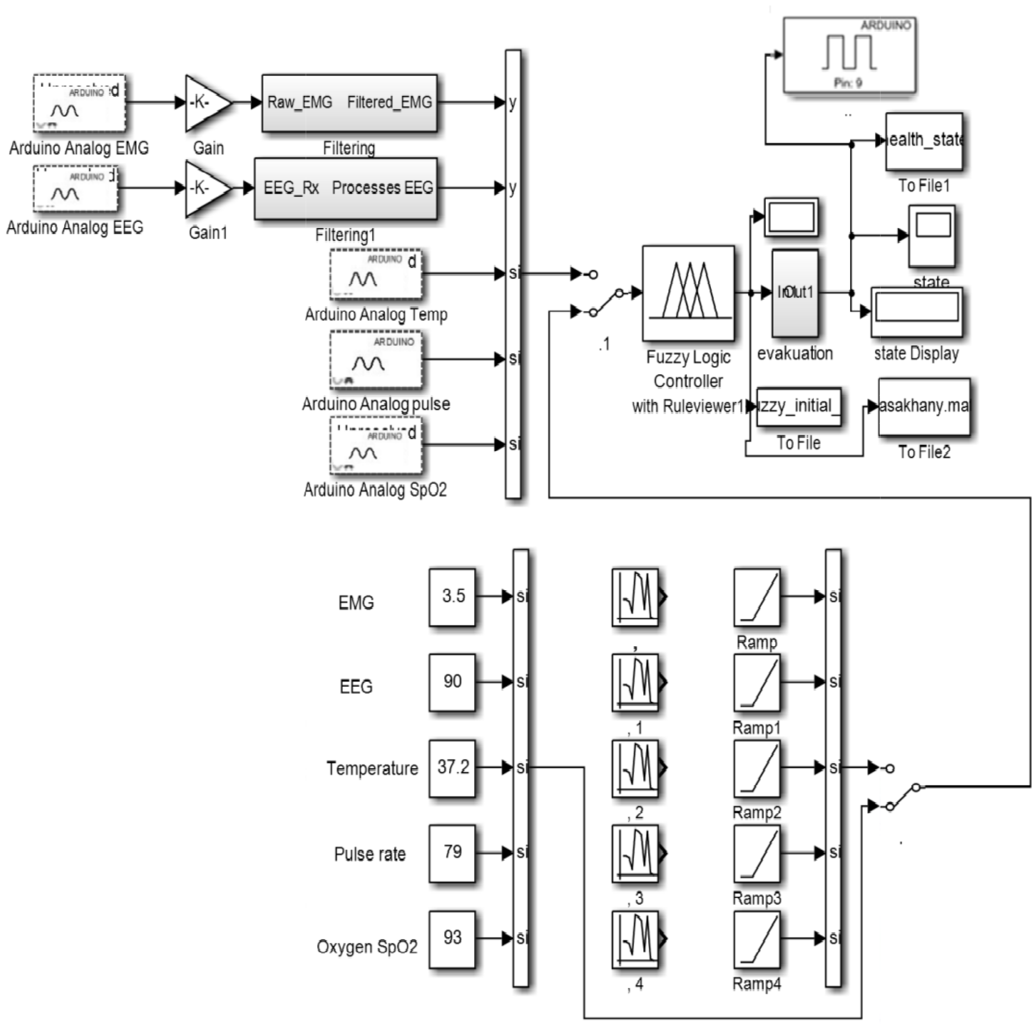

Figure 9: Hardware Inloop Simulation

7. CONCLUSION

This study proposes AI strategies for diagnosing COVID-19 symptoms in a very short period of time with high accuracy, overcoming several limitations of existing AI. The project entails the modelling, hardware design, and validation of a complex AI diagnostic system. The method used an artificial fuzzy inelegance to determine a patient's COVID-19 health status and discriminate between other nearby symptoms and COVID-19 infected people. Furthermore, the system provides a report containing the health condition and the level of medical care required without any human intervention in a significantly short time (seconds), allowing the examination of a large number of people in a relatively short time without incurring any operating costs. The device examines a variety of important biological and human functions before analysing the data and issuing a complete report on the state of the patient's health. Hardware designs are used to identify appropriate components for system and software integration. The suggested system is examined and tested using an experimental research. The findings demonstrated that the suggested approach might be utilised to differentiate between healthy and infected persons prior to the manifestation of COVID-19 symptoms.

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