Revista Argentina de Clínica Psicológica
2021, Vol. XXX, N°2, 103-109
DOI: 10.24205/03276716.2020.4010

Artificial intelligence for digenesis and controlling the Coronavirus

Ashraf Elfasakhany[a*]

Abstract
In this research article, monitoring, diagnosing, and efficiently reducing the spread of the virus are carried out by artificial intelligence (AI) techniques. The work resolved a number of issues and weaknesses of the early AI methods. The AI is developed and investigated to provide a detailed report on the case/patient without human/doctor intervention. The current work also designs a device for the rapid examination (seconds) of the human (potential patient), thereby facilitating the observation of a large number of people in a short period without running costs. The suggested system tests a number of human functions, including neurotransmitter and brain status, mood/mental states, facial muscle tension level, temperature of the body and hands, pressure and pulse rates, blood oxygen level, breathing rate and their difficulties, eye(s) redness level, and overall body imbalances. The collected data are analyzed and a detailed report on the patient condition is issued. The diagnosis system utilized artificial fuzzy inelegance via applying four test cases: mild, moderate, severe, and critical cases. The level of medical care according to the case is distinguished considering intensive care and/or resuscitation and, in turn, the health case is controlled.
Keywords: Coronavirus; controlling; artificial intelligence; digenesis.

1. Introduction

The importance of AI not only applies in discovering of the disease but also in the diagnosis. The AI system can use a camera based on computer vision and infrared sensors to predict the temperature of people in public areas. The system, which is currently used in railway stations, can check up to 200 people a minute and detect their temperature in the range of ±0.5 °C, e.g., the system indicates people with abnormal temperatures. The AI system was recently developed to detect the virus in computerized tomography (CT) of a patient's chest. The developers of the system indicate approximately 96% diagnostic accuracy, providing results in a considerably short time (less than 15 min). The system can also quickly identify the differences between emerging Covid-19 and ordinary pneumonia. Currently, about 100 hospitals in China are relying on such system.

One of the challenges of using CT image analysis is distinguishing between Covid-19 patients and other types of pneumonia. Differentiating between some types of pneumonia and the Coronavirus is generally difficult due to the considerable similarity between the symptoms. Covid-19 has almost identical posterior distribution and topography images with substantially close ground-glass opacities and multifocal [1–6]. Xie et al. [7] and some other researchers worked on such a topic by adding several fully connected layers for patient classification process. Song et al. [8] improved a feature network and attention module for such process. Lin et al. [9] provide a complex network but a represented fine-grained image aspects. Gozes et al. [10] investigated a commercial medical program for image processing with fine-tuned Covid-19 cases to classify the images of Covid-19 ones. Overall, the researchers generally showed the potential of distinguishing Covid-19 from other diseases.

Recently, researchers have reported speech or sound-based Covid-19 pneumonia detection techniques. In such techniques, instruments are applied to check dry and wet coughing or sneezing sounds, speech under cold sounds, eating behavior sounds, and sleepiness or pain sounds. Sound processing is subsequently analyzed via paralinguistic computation [11]. Cell phones are also capable of detecting Covid-19 patients [12]. The sound technology problems, however, include detection of coughing, breathing difficulties, and

[a]Mechanical Engineering Department, College of Engineering, Taif University, P.O. Box 11099, Taif 21944, Saudi Arabia.
**Correspondence: ashr12000@yahoo.com; a.taha@tu.edu.sa; Tel.: +966 (02) 7272020; Fax: +966 (02)7274299*

sneezing.

The above overview shows dissimilar methods for Covid-19 diagnosis. The disadvantages of such methods, however, are their diagnosis after symptoms appears. This causes a great virus spread and uncontrolled conditions. In addition, the methods could not evaluate the health condition of patients without doctors' involvement, which causes many doctors' infection with the virus. This study aims to overcome such problems by improving the existing AI techniques. AI is developed in this study to determine the infection time of patients with the virus and the level of medical care needed and then release a detailed report on the case without human intervention. This work also designed, built, and tested a device to examine Covid-19 (potential patients) in a rapidly fast time (seconds), which allows the examination of the largest number of people in a short period without running cost. The proposed device measures many vital biological and human functions and the data are analyzed and a detailed report is released regarding the health conditions. This study among the research of enhancing public health and improving the environmental problems [13–38].

2. Proposed system methodology and working principle

The methodology principle aims to determine the patient infected with the Coronavirus and report the level of medical care needed for further assessment and/or treatment. Bio-signals, in conjunction with other criteria as physiological indicators, are considered to evaluate the health and severity conditions. The design includes measurements of human bio-signals and physiological indicators of body temperature and pulse rate of the heart. In addition, the vital biological human functions are evaluated via the mental state of the brain, tension level of face muscles, hand/body temperature, rate of pulse and pressure, oxygen level in the blood, and difficulty of breathing. The electromyogram (EMG) signals are acquired from the muscle, while electroencephalography (EEG) signals are acquired from the brain. The suggested system for EEG signals would be placed as a wearable on the head, while EMG signals would be placed around the hand wrist. Meanwhile, the bio-data of humans could be read from the front and top of the head. The collected bio-data is analyzed via artificial fuzzy algorithm. The continuous intelligent fuzzy logic algorithm takes a decision based on standard rules of a healthy person. The state of human health is then defined and a recommendation is provided for the medical care needed considering intensive and/or resuscitation. The recommendation is displayed on an LCD together with soft light and sound notification. Synergistic integration with embedded methodology is considered in the system design as discussed later.

Table 1. **The initial applied values for ramp input block.**

Test №	EMG	EEG	temp	Pulse rate	SpO2	slope
(1)	2	65	35	55	75	2
(2)	2.5	75	36	50	70	1

Table 2. **Input reading examples on Bio-signals and Physiological indicators, and heath state evaluation results.**

Test №	Temp	Pulse rate	Oxygen Level SpO2	EMG	EEG	Decision numerical value	Color To switch	Health State
(1)	37	70	90	3.4	86	1.2	Green	Ok
(2)	37.5	75	85	3.1	93	1.65	Green	Ok
(3)	38.5	80	95	2.4	83	3.672	red	Hyp
(4)	40	75	80	-	-	5.4	Red	ICU
(5)	36	95	85	3.8	81	4	Red	Hyp
(6)	38.6	100	80	2.5	78	4.73	Red	ICU

3. Overall design and prototyping

A personal PC, MATLAB-Simulink, Arduino GUI, and Microsoft Excel software are all regarded as tools to test systems, subsystems, modules, circuits, and the overall system operation. Additionally, testing of acquired data for saving and analysis is considered. An experimental setup for such tests is conducted as shown in Figure 1. The MATLAB/Simulink models for data reading, processing, and programming of fuzzy algorithm are shown in Figures 2 and 3. Most of the selected input sensors are analog types, except for the temperature sensor. Software integrations, along with manufacturer programming libraries, Arduino GUI, and Microsoft Excel software, are used to read and process the sensor signals.

Considering electrodes with microvolt signals, EEG measures brain electrical activity; EMG measures electrical impulses produced by muscle fibers. Covid-19 infection causes facial muscle pains, but, generally, the pains in muscle can also be attributed to exercise. Thus, it is important to differentiate between pains from Covid-19 and other causes. The pains caused by Covid-19 are sharp, incapacitating, and persistent. In addition, muscular symptoms linked to Covid-19 include myalgia (muscle pains and tiredness) and headache, which could be measure by EMG and EEG. Figure 4 shows EEG channel unit applied to read the human brain electrical activities. The Mind-Flex circuit chip is applied, as shown in Figure 5, for signal acquisition and processing (signal filtering and amplifying) of the microcontroller through pins. This set is considered to read human health conditions by interpretation and relation of the mind state with taking into account the stress, relaxation, and drowsy conditions. Software integration is applied to read such three state conditions in terms of reading range between 0% and 100%. A high value leads to warning condition; the three selected states are interrelated as 0% in fully relaxation and 100% in full attention condition. The Myo-Ware module EMG, as shown in Figure 6, is a ready-made segment to read, filter, and rectify the electrical impulse produced through muscle fibers. The module was designed to wire directly into the microcontroller modules, as shown in Figure 7. The output voltage of the sensor is proportional to the muscle activities [39]. Depending on muscle function, programing integration is implemented for reading ranges between 0 and 5 VDC [40].

The linguistic variables are considered as follows. Considering EMG with a range between 0 and 5, the variables are denoted as [L, M, and H]. EEG drowsy, relaxed, and attention, ranging between 0 and 100, is respectively denoted as [D, R, and A]. Body temperatures of low, normal, fever, high fever, and extremely high showed a range between 33 and 45 and are respectively denoted as [L, N, F, HF, and EH]. Heart pulse rate in normal and/or high infection in a range between 55 and 110 is denoted as [N, IN, and HIN]. Oxygen levels in a severely low and/or normal range between 70 and 100 are denoted as [SL, L, and N]. The output health state with no care needed, hypnosis, intensive care, and resuscitation range is between 1 and 8 and denoted as [OK, HYP, ICU, and RES]. Examples of such cases are shown in Figure 8. The output membership function, ranges, and linguistic variables are shown in Figure 9. The fuzzy rules in the base and inference mechanism are designed to correlate all read input data of human bio-signals and indicators. Moreover, the decision expresses the Covid-19 infection, human health condition, and/or the suggested medical care. The MATLAB-Simulink models, as shown in Figures 2 and 3, are interfaced with the ATmega328p microcontroller of type Arduino-Nano board for the data acquisition, analysis, and proofing concepts. The microcontroller reads the values of different inputs of bio-signals and indicators, and the data are then interfaced into PC and MATLAB software for further processing and decision making. Figure 10 shows the Simulink model with different inputted values of all bio-signals and indicators of the final estimated results based on the fuzzy logic algorithm and visually displayed outputs.

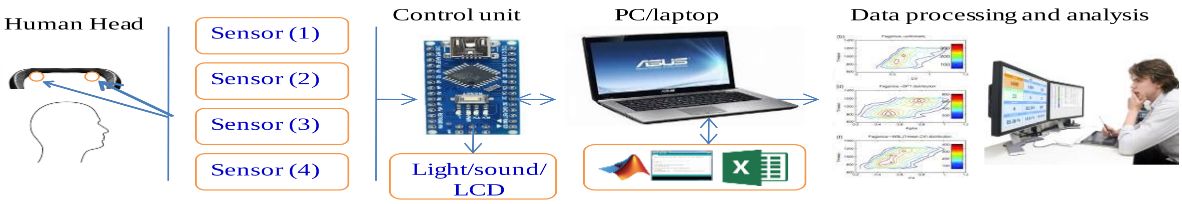


Figure 1. **Experimental setup represented pictorially.**

Figure 2. **Reading a sensor**

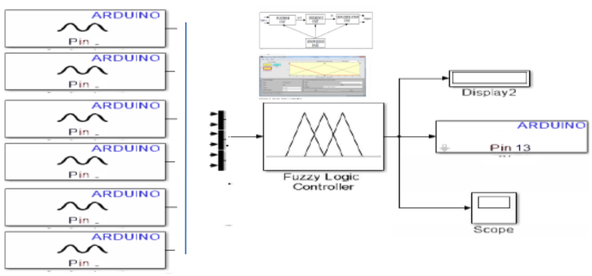


Figure 3. **Overall system MATLAB/Simulink model for data processing and programming fuzzy**

Figure 4. **The Mind-Flex headset EEG reading**

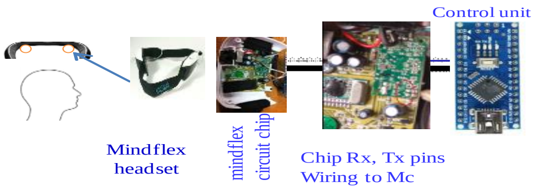


Figure 5. **Wiring Mindflex to microcontroller through pins**

Figure 6. **Myo-Ware module EMG reading**

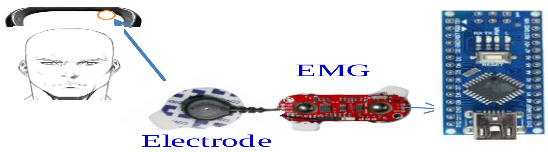
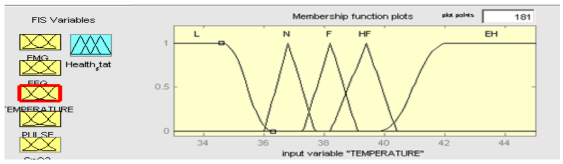


Figure 7. **MyoWare EMG module**

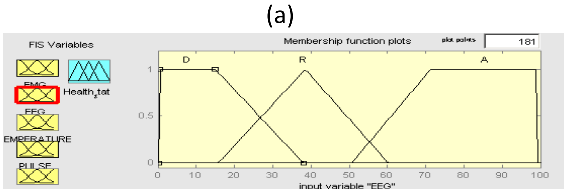
4. System testing results and discussions

Together with MATLAB-Simulink and fuzzy algorithm, different methods are considered to test working conditions and the level of correctness of the results: (a) a constant input value is used as input for each sensor to represent the reading of each bio-data and indicator; (b) a ramp Simulink block with different slope values is used to evaluate the model in different inputs with changing and/or increasing rates. A couple of examples of graphical results are shown in Figure 11 at ramp input values. As seen, the applied ramp block slope is 2 and then 1 with corporate to initial values. Table 1 summarizes the initial applied values for ramp input block. By analyzing the input values, the results of decisions obtained by the fuzzy algorithm show that the algorithm could be used with the bio-data in conjunction with other criteria, mainly physiological indicators, to distinguish between healthy and infected persons. Additionally, these results would be used to determine when the person is infected with coronavirus and then report the level of medical care needed considering intensive care and/or resuscitation. In particular, Table 1 shows the results of test (1), which reveals that the person needs hospital intervention for initial medical care based on the preliminary values of bio-data and indicators. The values reached normal levels with increasing input values of bio-data and physiological indicators in a ramp fashion; thus indicating that health care is unnecessary. The values reached the level of necessary hospitalization for medical care with further increasing values of bio-data and physiological indicators in a ramp fashion. Further increase in values also raises the level of intensive care (ICU) requirement. As shown in Table 1 and Figure 11, similar conclusions can be made in test (2).

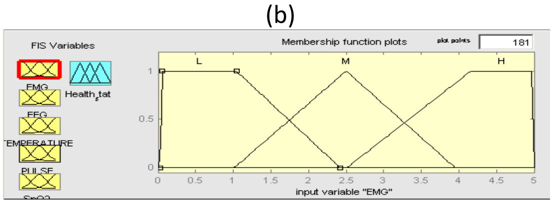
By analyzing the two cases, Table 2 shows that the results and the decisions taken are satisfied considering input readings. In particular, the input data are informative and intuitive; such data can intuitively demonstrate the decision of the human health state and recommendations considering the level of required medical treatment. It is important to highlight that the system might be required to evaluate in a real test case with a person infected with covid-19; however, this would be carried out in the next stage of this work; presenting a design and prototype of Covid-19 with minor tests are quite satisfactory in this stage.



(a)



(b)



(c)

Figure 8. **Examples on used membership functions type, ranges and linguistic variables; (a) Body temperatures, (b) EEG, and (c) EMG**

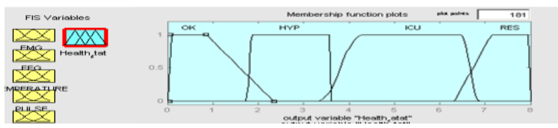


Figure 9. **The output membership functions, ranges and linguistic variables: [OK, hypnosis, intensive care, or resuscitation].**

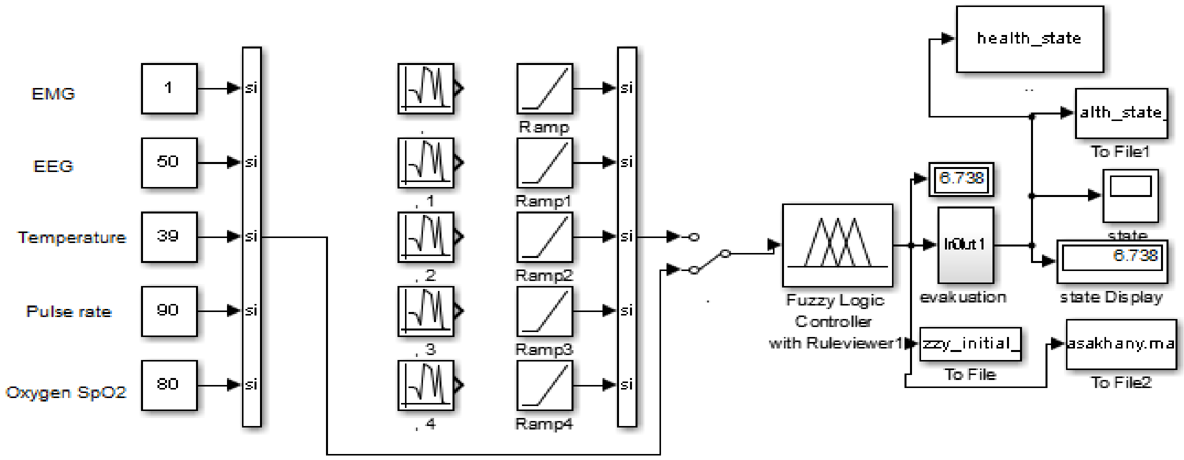
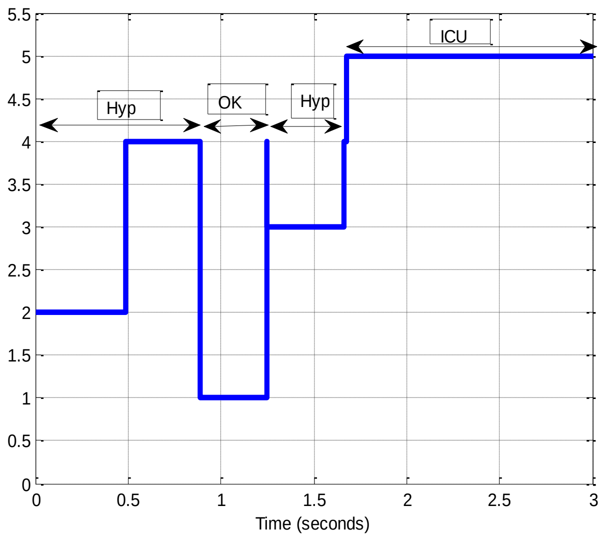
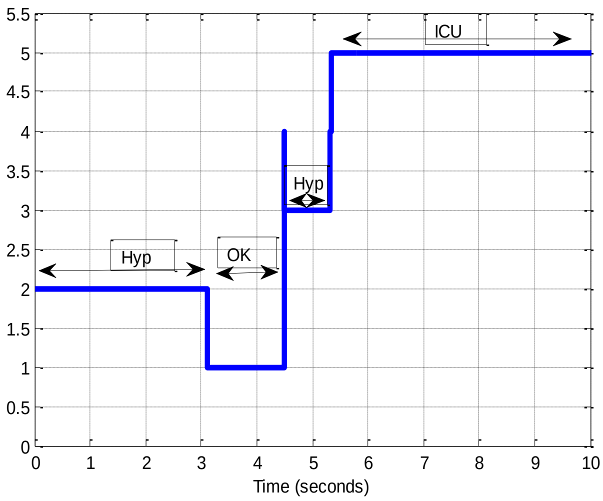


Figure 10. **Simulink model for fuzzy algorithm testing with inputs and outputs developed in MATLAB/Simulink.**



(a): Test (1)



(b): Test (2)

Figure 11. **Two graphical examples on testing results when the all input readings are increasing ramp inputs as in Table 1.**

5. Conclusions

The current work improves AI techniques with high precision for the diagnosis of Covid-19 through solving some problems of the available AI. Such developments in AI techniques have not been introduced early. Simulation, hardware design, and validation of a sophisticated AI diagnosis device are covered in this work. The AI is built via artificial fuzzy inelegance and can differentiate between Covid-19 and other diseases in close symptoms. In addition, the AI offers a report containing the health condition and the level of medical treatment required in a considerably rapid period (seconds) without any human interference; this allows multiple patients to be examined without running costs in a significantly short time. The developed technique is designed based on monitoring many important biological and human functions, such as the brain situation and neurotransmitters, mental/mood disorders, the level of facial muscle tension, the temperature of the hands and body, the rate of pulse and pressure, the level of oxygen in the blood, the rate of breathing and its difficulty, the degree of redness of the eye(s) and the overall imbalance of the body. The proposed AI method with the artificial fuzzy algorithm could be used to differentiate between healthy and infected individuals.

Acknowledgments

This work was supported by Taif University researchers supporting project number (TURSP-2020/40), Taif University, Taif, Saudi Arabia.

Conflict of Interest

There are no conflicts of interest in this study.

References

[1] V. M. Corman, O. Landt, M. Kaiser, R. Molenkamp, A. Meijer, D. K. Chu, et al., "Detection of 2019 novel coronavirus (2019-nCoV) by real-time RT-PCR," Eurosurveillance, vol. 25, 2020.

[2] D. K. Chu, Y. Pan, S. Cheng, K. P. Hui, P. Krishnan, Y. Liu, et al., "Molecular diagnosis of a novel coronavirus (2019-nCoV) causing an outbreak of pneumonia," Clinical chemistry, 2020.

[3] N. Zhang, L. Wang, X. Deng, R. Liang, M. Su, C. He, et al., "Recent advances in the detection of respiratory virus infection in humans," Journal of medical virology, vol. 92, pp. 408-417, 2020.

[4] M. Chung, A. Bernheim, X. Mei, N. Zhang, M. Huang, X. Zeng, et al., "CT imaging features of 2019 novel coronavirus (2019-nCoV)," Radiology, p. 200230, 2020.

[5] M. Hosseiny, S. Kooraki, A. Gholamrezanezhad, S. Reddy, and L. Myers, "Radiology perspective of coronavirus disease 2019 (COVID-19): lessons from severe acute respiratory syndrome and Middle East respiratory syndrome," American Journal of Roentgenology, pp. 1-5, 2020.

[6] S. Salehi, A. Abedi, S. Balakrishnan, and A. Gholamrezanezhad, "Coronavirus Disease 2019 (COVID-19): A Systematic Review of Imaging Findings in 919 Patients," American Journal of Roentgenology, pp. 1-7, 2020.

[7] X. Xie, X. Li, S. Wan, Y. Gong, Mining X-ray images of SARS patients. Data Mining: Theory, Methodology, Techniques, and Applications, Williams, Graham J., Simoff, Simeon J. (Eds.), pp. 282-294, ISBN: 3540325476, Springer-Verlag, Berlin, Heidelberg, 2006.

[8] Y. Song, S. Zheng, L. Li, X. Zhang, X. Zhang, Z. Huang, J. Chen, H. Zhao, Y. Jie, R. Wang, Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT images. medRxiv preprint medRxiv:2020.02.23.20026930, 2020.

[9] T.-Y. Lin, P. Dollar, R. Girshick, K. He, B. Hariharan, S. Belongie, Feature pyramid networks for object detection, In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2117–2125, 2017.

[10] O. Gozes, M. Frid-Adar, H. Greenspan, P. D. Browning, H. Zhang, W. Ji, A. Bernheim, E. Siegel, Rapid AI development cycle for the coronavirus (COVID-19) pandemic: Initial results for automated detection & patient monitoring using deep learning CT image analysis, arXiv preprint arXiv:2003.05037, 2020.

[11] B. Schuller and A. Batliner, Computational Paralinguistics: Emotion, Affect and Personality in Speech and Language Processing. Wiley, 2013.

[12] A. S. S. Rao and J. A. Vazquez, "Identification of covid-19 can be quicker through artificial intelligence framework using a mobile phonebased survey in the populations when cities/towns are under quarantine,"Infection Control & Hospital Epidemiology, pp. 1–18, 2020.

[13] Elfasakhany A. Modeling of pulverised wood flames. PhD thesis, fluid mechanics dept., Lund, Sweden, 2005; ISBN–13/EAN: 9789162864255.

[14] Elfasakhany A., Bai X.S. Modeling of Pulverised Wood Combustion: A Comparison of Different Models. Prog. Comp. Fluid Dynamics (PCFD) 2006; 6:188–199.

[15] Elfasakhany A, Tao L, Espenas B, Larfeldt J, Bai XS. Pulverised Wood Combustion in a Vertical Furnace: Experimental and Computational Analyses. Applied Energy 2013;112:454–464.

[16] Elfasakhany A., Klason T., Bai X.S. Modeling of Pulverised Wood Combustion Using a Functional Group Model. Combustion Theory and Modeling 2008; 12:883–904.

[17] Elfasakhany A. Alcohols as Fuels in Spark Ignition Engines: Second Blended Generation. Book, Lambert Academic Publishing, Bahnhofstrabe, Deutschland, Germany, 2017; ISBN: 978–3–659–97691–9.

[18] Elfasakhany A. Benefits and drawbacks on the use biofuels in spark ignition engines. Book, Lambert Academic Publishing, 17 Meldrum Street, Beau Bassin 71504, Mauritius, 2017, ISBN: 978–620–2–05720–2.

[19] Elfasakhany A, Bai XS. Numerical and experimental studies of irregular-shape biomass particle motions in turbulent flows. Engineering Science Technology 2019;22:249–265.

[20] Elfasakhany A. The effects of ethanol–gasoline blends on performance and exhaust emission characteristics of spark ignition engines. Int J of Automotive Eng 2014;4:608–620.

[21] Elfasakhany A. Investigation on performance and emissions characteristics of an internal combustion engine fuelled with petroleum gasoline and a hybrid methanol–gasoline fuel. Int J of Eng Tech 2013;13:24–43.

[22] Elfasakhany A. Experimental investigation on SI engine using gasoline and a hybrid iso-

butanol/gasoline fuel. Energy Convers Manage 2015;95:398–405.

[23] Elfasakhany A. Experimental study on emissions and performance of an internal combustion engine fueled with gasoline and gasoline/n-butanol blends. Energy Convers Manage 2014;88:277–283.

[24] Elfasakhany A. Investigations on the effects of ethanol–methanol–gasoline blends in a spark–ignition engine: performance and emissions analysis. Eng Sci Tech JESTECH 2015;18:713–719.

[25] Elfasakhany A, Mahrous A.F. Performance and emissions assessment of n-butanol–methanol–gasoline blends as a fuel in spark–ignition engines. Alexandria Eng Journal 2016; 55:3015–3024.

[26] Elfasakhany A. Engine performance evaluation and pollutant emissions analysis using ternary bio-ethanol–iso-butanol–gasoline blends in gasoline engines. J Cleaner Production 2016;139:1057–1067.

[27] Elfasakhany A. Experimental study of dual n-butanol and iso-butanol additives on spark–ignition engine performance and emissions. Fuel 2016;163:166–174.

[28] Elfasakhany A. Investigations on performance and pollutant emissions of spark–ignition engines fueled with n-butanol–, iso-butanol–, ethanol–, methanol–, and acetone–gasoline blends: a comparative study. Renewable & Sustainable Energy Reviews 2017;71:404–413.

[29] Elfasakhany A. Biofuels in Automobiles: Advantages and Disadvantages: A Review. Current Alternative Energy 2019;3:1–7.

[30] Elfasakhany A. Performance and emissions of spark–ignition engine using ethanol–methanol–gasoline, n-butanol–iso-butanol–gasoline and iso-butanol–ethanol–gasoline blends: a comparative study. Eng Sci Tech JESTECH 2016;19:2053–2059.

[31] Elfasakhany A. Performance and emissions analysis on using acetone–gasoline fuel blends in spark–ignition engine. Eng Sci Tech JESTECH 2016;19:1224–1232.

[32] Elfasakhany A. Gasoline engine fueled with bioethanol-bio-acetone-gasoline blends: Performance and emissions exploration. Fuel 2020: 274, 117825.

[33] Elfasakhany A. Dual and Ternary Biofuel Blends for Desalination Process: Emissions and Heat Recovered Assessment, *Energies* 2021: *14*(1), 61, 14010061

[34] Elfasakhany A., Alsehli M., Saleh B., Aly A., Bassuoni M. Renewable Pulverized Biomass Fuel for Internal Combustion Engines. Processes 2020: 8 (4), 465.

[35] Elfasakhany A. State of art of using biofuels in spark ignition engines. Energies 2021, 14, 779.

[36] Elfasakhany A. Exhaust emissions and performance of ternary iso-butanol–bio-methanol–gasoline and n-butanol–bio-ethanol–gasoline fuel blends in spark-ignition engines: assessment and comparison. Energy 2018:158, 830–844.

[37] Elfasakhany A., Tao L.X., Bai X.S. Transport of pulverized wood particles in turbulent flow: numerical and experimental studies. Energy Procedia 2014: 61, 1540–1543.

[38] Elfasakhany A. Powder biomass fast pyrolysis as in combustion conditions: Numerical prediction and validation. Renewable Energy Focus 2018: 27, 78-87.

[39] S. Ahmed, Intelligent Bio-Detector, Open Journal of Applied Sciences, 2016, 6, 903-937.

[40] A. Elfasakhany, M. Alsehli, F. A. Salem, Using artificial intelligence to determine the patient infection time with Coronavirus and report the level of medical care needed, Revista Argentina de Clínica Psicológica, Vol. 30, issue 1, 269-282, 2021.