

생체전기임피던스법을 이용한 코로나 사망률 예측 모델

신중훈[○], 홍충선^{*}

경희대학교 컴퓨터공학과
{michael, cshong}@khu.ac.kr

Evolvable COVID-19 Mortality Prediction Model Using Bioelectrical Impedance Analysis

Jong Hoon Shin[○], Choong Seon Hong^{*}

Department of Computer Science and Engineering, Kyung Hee University, South Korea

Abstract

As COVID-19 cases surges, most countries lack resources to conduct active monitoring for each patient without symptoms nor suspected patients. We propose a method to predict the possibility of developing severe symptom and mortality rates at the testing center to reduce the burden for healthcare workers and government officials conducting active monitoring and quarantine. Installing the BIA devices with the prediction model installed at the testing site for COVID-19 and encouraging suspected patients to conduct BIA will predict each patient's risk. The prediction result will allow healthcare workers to warn each individual of their risk and government officials to conduct active monitoring for the suspected patients with high-risk factors. The prediction model from our method will produce a more accurate result as our machine learning model updates each patient's progression, such as hospitalization, ICU admission, and death. The result will allow each patient to be aware of the danger they are facing and encourage responsible behavior as well as reduces the burden for both healthcare workers and government officials by allowing them to focus on more vulnerable.

1. Introduction

Coronavirus disease 2019 (COVID-19) is a global disease that led to over 1,490,000 deaths worldwide and 64,500,000 confirmed cases, leading to a devastating outcome [1]. As the COVID-19 case surpasses 60 million, it is getting harder to keep a close watch on each patient in quarantine and track their progress. We propose an evolvable method to evaluate each individual's risk at the initial testing stage, so healthcare workers or government officials can warn them to take extra caution or monitor those with higher risk. Our method is based on two key technologies, federated learning and Bioelectrical Impedance Analysis (BIA).

In most countries, aggregating patient data to a central location is prohibited due to patient privacy [2], whereas Machine Learning requires a large dataset to optimize the result. To overcome this challenge, we used federated learning to avoid locally aggregating patient data but harness the full potential of fragmented patient data from local hospitals across the country and even countries to have an outcome that is representative of a larger population.

According to [3], there are several key factors that are significantly associated with COVID-19 mortality: age, Body mass index (BMI), severe comorbidities, advanced respiratory support, and critical illness. Our approach to use BIA predicts the severity and mortality can be related to most key factors that are significantly associated with COVID-19 mortality [13,14,15].

The age, which is the factor that is the most transparent and easy to distinguish, will be a valuable input feature for model training. For

severe comorbidities, advanced respiratory support, and critical illness, these factors are medical details that are hard to confirm or only present after patients are hospitalized. But BIA is a widely used method to measure body composition to detect obesity, which is a known critical illness and disease that cause some of the most critical illness and led to severe comorbidities and advanced respiratory support [4,5,6,13]. Also, BIA devices calculate BMI with BIA. Thus, with BIA, we can produce a reliable result in COVID-19 mortality and severity prediction.

2. System Model

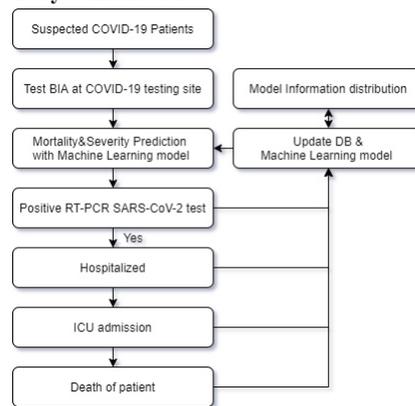


Fig.1. Study Model

Our method can be simplified into Fig. 1, a flowchart depicting how our method can predict mortality and severity of the suspected patient if the individual is tested positive for the Reverse Transcriptase-Polymerase Chain Reaction Severe Acute Respiratory Syndrome Coronavirus 2 (RT-PCR SARS-CoV-2) test.

2.1. Test BMI with body composition analyzer

BMI can be calculated with Eqn.1[7]. It is a very simple equation

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*Dr. CS Hong is the corresponding author.

that one does not need a machine to calculate. However, in our method, we are using a body composition analyzer to gather to improve the performance of the prediction model.

$$BMI = \frac{m}{h^2} \quad (1)$$

BMI means body mass index, m means mass (in kilograms), and h means height (in meters).

Even though due to technical limitations, it is not possible to get direct *in vivo* measurement of body components (BC), there are indirect methods and models to measure it. The most widely used model to measure BC for both clinical and non-clinical settings is the Bioimpedance analysis (BIA). BIA technique measures the characteristics of BC by calculating electrical properties from the transit time of a low-voltage electric current through the body [7]. The from measured electrical properties, we can get valuable information about body tissue and body composition parameters such as total body water (TBW, Eqn.2[8]) and fat-free mass (FFM, Eqn.3[8]). The test only takes about 60 seconds and has very few guidelines that need to be kept to produce accurate and reliable results, and it is a non-invasive and low cost, which is why it is popular for non-clinical usage.

$$FFM = 0.661 \frac{H^2}{R_{50}} + 0.200W - 0.32, \quad (2)$$

$$TBW = 0.40 \frac{H^2}{R_{50}} + 0.148W + 3.32, \quad (3)$$

R_{50} means resistance measured at 50 kHz (ohm), H means height (cm) and W means weight (kg).

Key input features from BIA are phase angle, impedance, and analysis from the BIA device. The phase angle is an input feature that depicts the ratio between intracellular and extracellular water. Due to its sensitivity to nutritional status and close association with cellular integrity compared to that of impedance, the phase angle is a valuable input feature to the prediction model. The result varies with nutritional and hydration status, but if tested individuals are in a healthy state, phase angle's range should vary between 6° to 7° , for athletes up to 8.5° . If the phase angle is below 5° , it indicates that the tested subject shows signs of a loss of cellular integrity [7].

As the name Bioelectrical Impedance Analysis suggests, bioelectrical impedance (Z, Ω) is one of the key input features in BIA as well as our prediction model. The bioelectrical impedance varies by the composition of tissue and the frequency of the current that is applied. With the variation of the bioelectrical impedance, the BIA device calculates the relationship between resistance (R, Ω) and reactance (Xc, Ω) [8], which represent the relationship between intracellular and extracellular fluids to the capacitance of the cell membrane to find phase angle (Eqn.4[7]). With these measurements, it is possible to produce results such as analysis of body composition, muscle-fat, and more.

$$Phase\ Angle(^{\circ}) = \frac{reactance}{resistance} (180/\pi), \quad (4)$$

Lastly, for the early stage of the model, analysis from the BIA device will be used to increase the accuracy of the model. At the early stage of the model, where the FL model had less training data to produce a reliable result, we used analysis from the BIA device to get information regarding TBW, skeletal muscle mass, and body fat mass. With these measurements, we can use the Random forest to produce meaningful results until enough data is collected to mature the FL model.

2.2. Acquiring additional data

Our model is designed to produce more accurate results than a decision tree with age and BMI as branches. This is possible by updating the model with additional input features such as hospitalization, ICU admission, death of the patient, and Electronic Health Records (EHRs) from the progression of COVID-19. From EHRs, we prioritize gathering blood tests, urine tests, and blood pressure for these data are structured numerical data [11].

2.3. Updating model

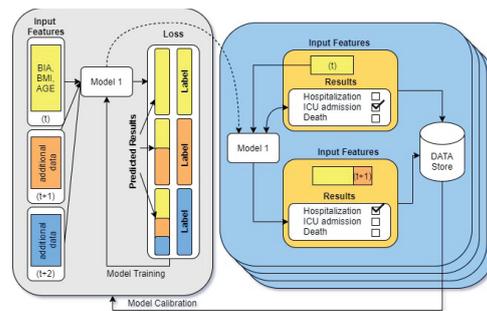


Fig. 2. Model Workflow

For we were not able to find any previous studies that utilize BIA with federated learning nor COVID-19, at the initial stage of the model, a Random Forest will be used to as sufficient data is gathered. The Random Forest model would be deployed at the BIA device on each testing site with proven input features such as age, BMI, BIA, and pre-existing conditions to evaluate the severity of the suspected patient if the patient tested positive for the RT-PCR SARS-CoV-2 test.

If we gathered enough BIA datasets to generate the initial model at a time (t), the model is trained with input features that will be consist of age, height, BMI, BIA result, BIA analysis result, and patients' progression (not severe, hospitalization, ICU admission, and death). The input features will increase as we have more data, such as blood tests, urine tests, blood pressure, etc. The trained model at the time (t) is then deployed at the BIA device on each testing site where it will produce a prediction of the suspected patient's severity of COVID-19 based on the input feature of time (t) by numbers from 0 to 3. The prediction result represents an estimated prediction of severity of the COVID-19, which varies from 0 to 3, 0 meaning not severe, 1 meaning hospitalized, 2 meaning ICU admission, 3 meaning death. The BIA result and prediction of the suspected patient will be stored in a temporary database until the suspected patient is tested positive. If patient is hospitalized it will update input value for patients'

progression and as test from hospital gets updated, it will be updated to the Data Store for the model calibration. If suspected patient is tested positive but not hospitalized, patient's data will wait for 21 days for 99 percentiles of patient develop symptom after 14 days of quarantine or active monitoring [10]. We allow full 14 days and additional 7 days for human error then update the data to the Data Store with patient's progression value as 0.

At the time ($t+1$), when we gathered enough data to utilize additional input features, we will extend the input features to improve the accuracy of the prognostic forecast. After extending the input features, we train the model with only ($t+1$) data. This process is scalable, thus allowing it to be an evolvable COVID-19 Mortality & Severity Prediction model.

After each update to the model, the local model sends weighted values to the central aggregator to update the global model.

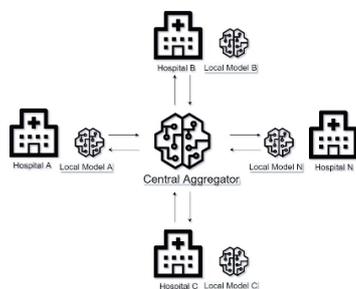


Fig. 3. Local FL model aggregation to global model

2.4. Attention Mechanism

For the model to expand input features and maximize the accuracy of the model, we adopted the Attention Mechanism to our model [9]. The basic concept is that each time the model tries to predict an output result, it only uses parts of an input features where the most relevant information is concentrated instead of an entire input features to focus on the few key values. Attention Mechanism is composed of two key components, the encoder and the decoder. How encoder for Attention Mechanism operates resembles that of the Encoder-Decoder Model but not for the decoder. During decoding, the decoder's hidden state is computed with a context vector for every output. Then attention vector is computed by context vector and attention function [12].

3. Conclusion and Future Directions

We propose an Evolvable COVID-19 Mortality Prediction model using Bioelectrical Impedance Analysis. It utilizes proven correlation and analysis to estimate severity and mortality risk by COVID-19 of each individual with just a minute. We believe this method can focus on limited government officials and healthcare workers to focus on individuals with higher risk as well as reduce unsafe behaviors from those with higher risk. For our method is focused on BIA and body composition, which is closely related to the endocrine diseases, we would like to evolve it to be able to conduct prognosis on individuals. Instead of numbers from 0 to 3, it would calculate the probability of developing each endocrine disease if this BIA result continues.

References

- [1] WHO Coronavirus Disease (COVID-19) Dashboard, World Health Organization.
- [2] United States. Department of Labor. Employee Benefits Security Administration. Health Coverage Portability: Health Insurance Portability and Accountability Act of 1996 (HIPAA). US Department of Labor, Employee Benefits Security Administration, 2004.
- [3] Hussain, Abdulzahra, et al. "Obesity and mortality of COVID-19. Meta-analysis." *Obesity research & clinical practice* (2020).
- [4] Kreissl, Alexandra, et al. "Clinically relevant body composition methods for obese pediatric patients." *BMC pediatrics* 19.1 (2019): 84.
- [5] National Heart, Lung, and Blood Institute. "Guidelines (2013) for managing overweight and obesity in adults: preface to the Expert Panel Report (comprehensive version which includes systematic evidence review, evidence statements, and recommendations)." *Obesity* (Silver Spring) 22.Suppl 2 (2014): S40.
- [6] National Heart, et al. Clinical guidelines on the identification, evaluation, and treatment of overweight and obesity in adults: the evidence report. No. 98. National Heart, Lung, and Blood Institute, 1998.
- [7] Marra, Maurizio, et al. "Assessment of body composition in health and disease using bioelectrical impedance analysis (BIA) and dual energy X-ray absorptiometry (DXA): a critical overview." *Contrast Media & Molecular Imaging* 2019 (2019).
- [8] Wan, Ching S., et al. "Bioelectrical impedance analysis to estimate body composition, and change in adiposity, in overweight and obese adolescents: comparison with dual-energy x-ray absorptiometry." *BMC pediatrics* 14.1 (2014): 1-10.
- [9] Vaswani, Ashish, et al. "Attention is all you need." *Advances in neural information processing systems* 30 (2017): 5998-6008.
- [10] Lauer, Stephen A., et al. "The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application." *Annals of internal medicine* 172.9 (2020): 577-582.
- [11] Vaid, Akhil, et al. "Federated learning of electronic health records improves mortality prediction in patients hospitalized with covid-19." *medRxiv* (2020).
- [12] Thar, Kyi, et al. "Evolvable Symptom-Disease Investigator for Smart Healthcare Decision Support System." *한국정보과학회 학술발표논문집* (2020): 578-580.
- [13] Kyle, Ursula G., et al. "Bioelectrical impedance analysis—part II: utilization in clinical practice." *Clinical nutrition* 23.6 (2004): 1430-1453.
- [14] Wan, Ching S., et al. "Bioelectrical impedance analysis to estimate body composition, and change in adiposity, in overweight and obese adolescents: comparison with dual-energy x-ray absorptiometry." *BMC pediatrics* 14.1 (2014): 1-10.
- [15] Heber, David, et al. "Clinical detection of sarcopenic obesity by bioelectrical impedance analysis." *The American journal of clinical nutrition* 64.3 (1996): 472S-477S.