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An Intelligent Framework to Predict Socioeconomic Impacts of COVID-19 and Public Sentiments

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Abstract

The outbreak of novel coronavirus (COVID-19) has extremely shaken the whole world. COVID-19 has increased human distress, damaged the global economy, flipped the lives of many people around the world upside down, and has had a huge effect on the health, economic, environmental, and social sectors. This study aims to determine the social and economic trends in the outbreak of COVID-19 in Pakistan. Machine learning techniques learn patterns from historical data and make predictions on its basis. Furthermore, an online survey has been conducted to collect data and a total of 410 responses are collected. Machine learning techniques have been used to highlight the impact of COVID-19 on daily life. Moreover, sentiment analysis on tweets of Pakistan has also been performed to evaluate the positive and negative sentiments of the people on COVID-19.

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1. Introduction

At the end of 2019, Wuhan City (China) experienced a rising number of unusual pneumonia cases. Such cases were reported to World Health Organization (WHO), and in January 2020, this novel coronavirus was named COVID-19. COVID-19 has infected 170 countries, with more than 41,043,648 confirmed cases worldwide and 1,129,596 people have died while fighting against this dreadful virus [1]. On March 11, 2020, WHO declared this COVID-19 as pandemic [2]. Governments around the world imposed social distancing measures, travel restrictions, border shutdowns, and quarantine in those countries which consist of the largest economies of the world. The COVID-19 spreads through the particular respiratory droplets when coughing, sneezing, or when people interact with each other. These droplets can be inhaled, or they can be stick on the surfaces that others may come in contact with, who can then get contaminated when they touch their eyes, mouth, or nose. This virus can live on different surfaces for some days (plastic and stainless steel) and few hours (copper and cardboard). The most common symptoms of this virus are fever, dry cough, or tiredness, and less common are body aches, diarrhea, sore throat, headache, etc. [3]. The symptoms are mostly experienced during 14 days. The countries which survived the first wave of COVID-19 are now experiencing the second wave of COVID-19 [4]. In Pakistan, the first two cases arrived on February 26, 2020, in Karachi and Islamabad on the same day, it was then confirmed by the Ministry of
Health of Pakistan [5]. Gradually these cases increased exponentially with total confirmed cases 319,317, 304,185 recoveries and 6,580 people died by fighting this deadly virus up till now (October 12, 2020). As the corona crisis arose in Iran, the government of Pakistan declared an emergency at the borders on the return of pilgrims. The government took preventive measures by imposing a lockdown in the country to control the spread of this viral infection. This lockdown affected the education system, led to the recession, financial issues, psychological issues, and Pakistan’s economy is badly affected, especially micro-small & medium-sized enterprises have faced severe issues in comparison with large enterprises [6]. Many healthcare professionals and workers have become the victim of mental distress, insomnia, anxiety, and depression [7]. Over the past few years, social media played an integral part in every individual’s life and serves as an implicit platform for people to share their interests with the people of the same mindset across the world. During this pandemic, people used social media platforms extensively used to express their feelings about the pandemic. P. Singh et al., aims to map people’s opinion on the COVID-19 pandemic all around the world, fear and hardships faced by them [8].

This study highlights two aspects of the COVID-19 outbreak. The first problem is to predict the impacts of COVID-19 on daily routine, monthly expense on protective gear, health, and social life. This problem of prediction has been considered as a classification problem, so this study is based on state-of-art supervised ML classification models such as Support Vector Classification (SVC), Logistic Regression (LG), Multinomial Naive Bayes Classifier (MNBC), and Random Forest Classifier (RFC). The learning models
have been trained using the data collected about socio-economic aspects of COVID-19. Whereas the second problem is to use Twitter data for sentiment analysis. This prediction aims to help the government and policymakers for a better response to the socio-economic aspects of the disease.

1.1. Motivation

The accurate prediction helps to estimate the impact of the COVID-19 pandemic on our socioeconomic sectors and suggests new strategies to overcome the losses caused by the virus. ML algorithms have been used to estimate the impacts of COVID-19 on socioeconomic [9] and sentiment analysis using Twitter data [10] by taking motivation from the discussed papers, this paper performed classification by using different techniques of ML as well as sentiment analysis.

1.2. Problem Statement

The lockdown in many countries due to COVID-19 disease has led to severe impacts on health, financial crisis, education, etc. There is fast-growing literature on evaluating the casual impacts relaxing/lifting the lockdown and socioeconomic impact of COVID-19, in both developed and emerging countries [11][12]. Also, huge amount of social media data related to the disease has not been utilized to propose a remedial solution [13]. There is a need to design a framework that explores the socioeconomic dynamics of COVID-19 using machine learning approaches and social media data to provide better accuracy and prediction.

1.3. Contribution

Our main contributions in this paper are the followings:
1. We have studied the impact of COVID-19 on daily routine, monthly expense on protective gear, health, and social life.

2. We have used the state of the art machine learning algorithms such as Support Vector Classification (SVC), Logistic Regression Classifier (LRC), Multinomial Naive Bayes (MNB), and Random Forest Classifier (RFC) to train using the data collected about socio-economic aspects of COVID-19 to help government officials and policymakers better respond to the socio-economic aspects of the disease.

3. Furthermore, sentiment analysis is performed on Twitter data, to analyze the public sentiments about COVID-19. Tweets were extracted against the hashtags “#COVID-19” and “#pandemic”. These terms were frequently used during the COVID-19 outbreak.

Organization of the paper: The rest of the paper is organized in following manner. In section-2 we will discuss the literature published on applications of machine learning approaches for COVID-19. Section-3 will present methodology, section-4 will show the results of our study and section-5 summarizes the paper with conclusion.

2. Related Work

Several science domains are facing a big challenge with the spread of COVID-19 around the globe. There’s a lot of ongoing studies to control and arrest the spread of this viral infection in various science domains. Thereby, to better understand and to take suitable measures for this pandemic, multiple estimating, prediction, modeling, and forecasting approaches are sug-
gested. For instance, many mathematical models are used to predict and estimate the rapid growth of confirmed cases [14].

One of the famous applications of Machine Learning in viral epidemiology is to make a prediction or statistical model that proved useful in the contamination of viruses such as Malaria, Ebola, Dengue, etc. B. E. Chekol and H. Hagras applied ML models to predict the outbreak of malaria in Ethiopia [15]. The study [16] used Multivariate Logistic Regression to formulate a prognostic model for the Ebola virus outbreak. In the context of COVID-19 pandemic, the study [17] emphasis the forecast of COVID-19 outbreak and early feedback, and [18] focuses on the live forecast of confirmed cases of COVID-19.

Several studies identified the impact of COVID-19 on the economy. The outbreak caused severe damage to the global economy [18, 19, 20, 21].

3. Design details of proposed scheme

3.1. Data Collection and Analysis

Data is obtained by online survey methods from Pakistan. In order to collect data, we used the snowball sampling method as used by [11], social media forums, and SMS advertisement service to float our form. As Urdu is the National Language of Pakistan, each question was translated into Urdu. A total of 36 questions were formulated to get a better response regarding COVID-19. Over 9 questions were about mental health, 19 questions were comprised of a daily routine before and during the pandemic, whereas a total of 4 questions were regarding expenditure on protective gear.
| Technique | Data set | Objective | Metrics | Limitation |
|-----------|----------|-----------|---------|------------|
| LSODA [12] | National Household Sample Survey (PNAD), Brazilian Institute of Geography and Statistics (IBGE), Health Informatics Department of the Brazilian Ministry of Health (DATASUS) and COVID-19 cases reported by State Secretaries of Health | Predicting mortality and outbreak of COVID-19 | MAE, RMSE | Actual data unavailability |
| ARIMA [14] | John Hopkins University | Predicting prevalence of COVID-19 | ACF, PACF | Availability of less data |
| SVR, ANFIS [15] | WHO | Predict the malaria epidemic up to three months ahead | RMSE, $R^2$ | Uncertainties are not handled |
| Multivariate Logistic Regression [16] | EVD dataset | Prognostic model for Ebola virus | AUC, $R^2$ | Limited data |
| ES [17] | Johns Hopkins University | Forecast of actual confirmed cases of COVID-19 | MPE | Potential inaccuracies in the actual data |
| ARIMA, LASSO, RS [18] | CSSE at Johns Hopkins University | Early forecasting of upcoming infected cases, recoveries and deaths of COVID-19 | MAR, MASE, RMSE, $R^2$ Score, $R^2$ Adjusted | Real-time data |
| ARIMA, WT, ORT [19] | Center for Systems Science and Engineering (CSSR) at Johns Hopkins University | Real-time forecast of daily confirmed cases of COVID-19 and risk assessment | MAR, RMSE | Limited data |
| Exponential Growth Model, DT, RF, LR, SVM [20] | WHO, World Bank website, Weather Underground | Predicting early containment of COVID-19 | Precision, Recall, Accuracy, F1 Score, ROC | Data till March 26, 2020 |
| ARIMA [21] | NIH | Short-term forecast of COVID-19 confirmed cases, deaths and recoveries | AIC | Limited data from 26 February to 12 April |
The study is based on the primary data collected through an online questionnaire related to the impact of COVID-19 on socioeconomic life in Pakistan. The respondents were those who have access to internet services. Due to the time constraints total of 410 individuals participated in the online survey form. The table 2 shows the distribution of the respondents gender-wise, age-wise, city-wise, etc.

Table 2: Profile of Participants

| Variable | Description | Frequency | Percentage |
|----------|-------------|-----------|------------|
| Gender   | Male        | 228       | 55.6       |
|          | Female      | 178       | 43.5       |
|          | Prefer not to say | 4 | 0.9 |
| Age      | 1-13        | 2         | 0.49       |
|          | 14-18       | 12        | 2.93       |
|          | 19-25       | 246       | 60         |
|          | 26-40       | 132       | 32.19      |
|          | Above 40    | 18        | 4.39       |
| Education| Primary     | 2         | 0.5        |
|          | Secondary   | 31        | 7.6        |
|          | Intermediate| 4         | 0.9        |
|          | Bachelors   | 194       | 47.3       |
|          | Masters     | 159       | 38.8       |
|          | Doctors     | 20        | 4.9        |
| Occupation| Student     | 240       | 58.5       |
|          | Employees   | 121       | 29.5       |
|          | Business    | 31        | 7.6        |
|          | Other       | 18        | 4.4        |
| City     | Islamabad  | 76        | 18.5       |
|          | Quetta      | 53        | 12.9       |
|          | Rawalpindi  | 50        | 12.2       |
|          | Faisalabad  | 32        | 7.8        |
|          | Karachi     | 31        | 7.6        |
|          | Lahore      | 31        | 7.6        |
|          | Peshawar    | 19        | 4.6        |
|          | Multan      | 10        | 2.4        |
|          | Other       | 108       | 26.3       |
| Lifestyle| Urban       | 348       | 84.8       |
|          | Rural       | 62        | 15.2       |
3.2. Machine Learning Methods Used

ML methods such as SVC, LR Classifier, Multinomial NB, and RF Classifier have been used for the classification, and results are compared in terms of accuracy. The results obtained from the models are analyzed. For the validation of results, accuracy is being used. LR Classifier outperforms in terms of accuracy (96%).

SVM relies on the principle of statistical learning that there exists an infinite line that isolates the two groups, known as hyperplanes. SVM algorithm aiming to find the right one that helps to reduce the error of classification on uncertain data. SVM search for the maximum marginal hyperplane (MMH) i.e. hyperplane with the greatest margin [18]. A hyper-plane that separates can be estimated as:

\[ H = W \cdot X + b = 0 \]  
(1)

Equation 2 denotes the the standard logistic function definition [22].

\[ \log[p/(1-p)] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i \]  
(2)

here \( p \) is the calculated probability of the outcome of event, \( \beta_0 \) is known to be the intercept term, \( \beta_1, \ldots, \beta_i \) are termed as the regression coefficients which is correlated with predictors \( x_1, \ldots, x_i \) correspondingly, and \( i \) represents the \( ith \) predictor. The following algorithm 1 shows step by step process of LR classifier:

The “Multinomial Naïve Bayes” term infers that every \( p(f_i/c) \) is a distribution of multinomial furthermore holds better for the ordinal values. In essence, the MBN model is an exceptional prototype of the Naïve Bayes technique, where a multinomial distribution has been used for each of its
Algorithm 1 Algorithm of LR

1: Begin
2: Input Variables ← read dataset,
3: Split 'Feature' ← Training (0.75%) & Testing (0.25%)
4: C ← 1.0
5: Intercept_Scaling ← 1
6: Max_Iter ← 500
7: Verbose ← 0
8: n_jobs ← 1
9: LogisticRegressionCV.fit(Data_Train, Target_Train)
10: Prediction ← LogisticRegressionCV.predict(Data_Test)
11: End

properties. The equation is given by:

\[ p(f_1, ..., f_n/c) = \prod_{i=1}^{n} p(f_i/c) \]  

(3)

3.3. Proposed Methodology

The term socioeconomic is very broad. But in this study mental health issues, the expense incurred on the protective care and daily routine of the people has been debated and predicted. The data is collected from students, employees, and businessmen by using the cross-sectional method. The data has been collected from different cities of Pakistan. The data was preprocess by applying feature selection techniques, to detect dominant features that play a significant role in prediction. Machine Learning models are implemented to predict the socioeconomic impacts of the COVID-19 pandemic.
The results extracted by the models are compared by applying evaluation measures. The model that performed better in terms of accuracy is highlighted.

Today, people use social media extensively to express their feelings. For this purpose, we gathered Twitter data for sentiment analysis purposes. This huge amount of data is used to analyze sentiments on COVID-19 and the socioeconomic impacts of COVID-19. These analyses will help the government and policy-makers to better understand and respond to this disease. The following proposed system model figure 1 explains the framework of the study step by step.

4. Simulations Results

4.1. Preprocessing Data

For this study, data was gathered by an online survey form. Total 410 responses were collected from different cities of Pakistan. The online form had also Urdu translation, to make it easy to understand. Data were split
into training and testing, seventy-five percent of the data is taken for training and twenty-five percent of the data is taken for testing.

4.2. Feature Selection

To select accurate and important features to form the data, feature selection is applied. Feature selection is done by RF [15]. Best features have the highest value of importance and have a greater effect on the output, after selecting the best features it is then given to the prediction. The threshold for the important features is set 0.005. Figure 2 shows the best features for General_Observation_Pandemic selected by RF.

4.3. Results

These important features are then selected for further prediction. Generally pandemic has impacted highly, slightly, and normally the health, income, and social life of the people. The results show LR Classifier outperforms in terms of accuracy 96%, followed by RF Classifier with the accuracy of 93%,
SVC gives the accuracy of 91% and whereas MultinomialNB gives the accuracy of 65% (shown in figure 3). Figure 4 displays the prediction result of SVC, LR Classifier, MultinomialNB, and RF Classifier.

During COVID-19 outbreak, people used internet for many purposes. In Pakistan, people ordered food at home while obeying SOPs (Standard Op-
Figure 4: (a), (b), (c), and (d) shows the predicted result of SVM, LR Classifier, Multinomial NB and RF Classifier on general perspective about COVID-19 outbreak.
The results in figure 5 shows LR Classifier outperforms in terms of accuracy 95%, followed by SVC with the accuracy of 93%, RF Classifier gives the accuracy of 89% and whereas Multinomial NB gives the accuracy of 81%. The predicted result of SVC, LR Classifier, Multinomial NB and RF Classifier is shown in figure 6.

During the lockdown, people ordered clothes, groceries, shoes, medical aid, etc through online websites and mobile apps. Figure 7 shows the comparison of classification techniques in terms of accuracy. LR Classifier shows 97%, followed by RF Classifier gives 93%, SVC leaves with 92% and Multinomial NB gives 78%. The result in figures 8 shows a slightly change in the routine of online shopping.

The government of Pakistan was forced to lock down mosques, huge get-togethers, private institutions, universities, shopping malls, marriage halls to avoid the prevalence of this viral infection. Figure 9 explains LR Classifier (94%) outperforms in terms of accuracy, both SVC and RF Classifier shows 92% accuracy, and MNB classifier gives the accuracy of 86%. The results confirms the inflation in COVID-19 infected cases, was due to the most people
Figure 6: (a), (b), (c), and (d) show the classified result of SVM, LR Classifier, Multinomial NB and RF Classifier on the impact of online food ordering due to this outbreak.

Figure 7: ML models accuracies for change in online shopping.
Figure 8: (a), (b), (c), and (d) shows the predicted result of SVM, LR Classifier, Multinomial NB and RF Classifier on change in online shopping routine due to COVID-19 outbreak.
preferred to stay home. As shown in figure 10 highest peak of 'Strictly avoided'.

![Bar chart showing ML models performance](chart.png)

Figure 9: ML models performance to determine the impact of lockdown on gatherings like family dinners, birthdays, funerals etc.

COVID-19 has sparked fear of economic and social crisis. Many businesses wrecked due to the COVID-19 pandemic. Figure 11 shows the fear of educational loss, loss of social life, loss of health, loss of income and loss of business.

COVID-19 has developed a fearful atmosphere for people all over the world due to its extremely contagious nature. In Pakistan, COVID-19 significantly affected mental health of health professionals, nurses, and other individuals. In this study, the figure 12 presents the psychological factors before COVID-19 rated by respondents and figure 13 shows the psychological suffering during the pandemic.

The only solution to prevent from this virus is social distancing and usage of protective gear. This may have increase expenditure to avoid prevalence of this virus. The comparison of expenditure on protective gear before and during the COVID-19 is shown in figure 14.
Figure 10: (a), (b), (c), and (d) shows the predicted results of SVM, LR Classifier, Multinomial NB and RF Classifier on going out on gatherings or meet-ups during pandemic.

Figure 11: Fear caused due to COVID-19 pandemic.
Figure 12: Mental health rated before COVID-19 pandemic.

Figure 13: Mental health rated during COVID-19 outbreak.

Figure 14: The comparison of expenditure on protective gear before and during COVID-19 outbreak.
4.3.1. Sentiment analysis using Twitter data

In this work, 1500 tweets were fetched by using the hashtags of “#COVID-19” and “#pandemic” from Twitter api. The tweets were gathered on November 2020. The most frequently used words on Twitter about COVID-19 are shown on figure 15. The negative and positive sentiments regarding the COVID-19 are shown in figure 16.

Figure 15: Word cloud based on COVID-19 outbreak.

Figure 16: Negative and positive sentiments of people about COVID-19 outbreak.

5. Conclusion

COVID-19 brings a peculiar social and economic challenge for the whole world. In this paper, ML-based prediction framework has been proposed to predict the socioeconomic impacts of COVID-19 on social life, mental health, 

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daily routine, and expenditure on protective gear. This study contains two aspects: prediction on socioeconomic impacts of COVID-19 and sentiment-analysis on COVID-19. ML classification techniques like SVM, LR Classifier, Multinomial NB and RF Classifier is used for the prediction of socioeconomic impacts of COVID-19 on daily routine, expenditure and mental health. It is inferred from the results of the classification techniques, SVM, LR Classifier, RF Classifier performed better than Multinomial NB in terms of accuracy. In future, other ML models as well as deep learning algorithms can be implemented for better analysis and results. Also an algorithm can be proposed with all the classification functionalities for analysis.

References

[1] Coronavirus Pandemic (2020), https://www.worldometers.info/coronavirus/ (Accessed on October 11, 2020).

[2] WHO — World Health Organization. https://www.who.int/. Accessed October 9, 2020.

[3] M. Yadav, M. Perumal and M. Srinivas, “Analysis on novel coronavirus (COVID-19) using machine learning methods”, Chaos, Solitons and Fractals, vol. 139, 2020, 110050, ISSN 0960-0779, doi: https://doi.org/10.1016/j.chaos.2020.110050.

[4] Covid-19: New fear grips Europe as cases top 30m worldwide, BBC News. (Accessed on October 11, 2020). https://www.bbc.com/news/world-54199825.
[5] COVID-19 Health Advisory Platform by Ministry of National Health Services Regulations and Coordination. (Accessed on October 11, 2020). http://covid.gov.pk/stats/pakistan.

[6] M. Shafi, J. Liu, W. Ren, “Impact of COVID-19 pandemic on micro, small, and medium-sized Enterprises operating in Pakistan,” Research in Globalization, vol. 2, 100018, ISSN 2590-051X, 2020, doi: https://doi.org/10.1016/j.resglo.2020.100018.

[7] R. P. Rajkumar, “COVID-19 and mental health: a review of the existing literature,” Asian Journal of Psychiatry, vol. 52, p. 102066, 2020, doi: https://doi.org/10.1016/j.ajp.2020.102066.

[8] P. Singh, S. Singh, M. Sohal, Y. K. Dwivedi, K. S. Kahlon and R. S. Sawhney, “Psychological fear and anxiety caused by COVID-19: Insights from Twitter analytics,” Asian Journal of Psychiatry, vol. 54, 2020, doi: https://doi.org/10.1016/j.ajp.2020.102280.

[9] S. Tuli, S. Tuli, R. Verma and R. Tuli, “Modelling for prediction of the spread and severity of COVID-19 and its association with socioeconomic factors and virus types,” medRxiv, 2020, doi: https://doi.org/10.1101/2020.06.18.20134874.

[10] L. Nemes and A. Kiss, “Social media sentiment analysis based on COVID-19,” Journal of Information and Telecommunication, 2020, pp. 1-15, doi: https://doi.org/10.1080/24751839.2020.1790793.

[11] E. H. S. Cardoso, M.S. Da Silva, F.E.D.A.F. Júnior, S.V. De Carvalho, A.C.P.D.L. Ferreira, D. Carvalho, N. Vijaykumar and C.R.L Francês,
“Characterizing the Impact of Social Inequality on COVID-19 Propagation in Developing Countries,” in IEEE Access, vol. 8, pp. 172563-172580, 2020, doi: https://doi.org/10.1109/ACCESS.2020.3024910.

[12] A. Ali, M. Ahmed, and N. Hassan, “Socioeconomic impact of COVID-19 pandemic, Evidence from rural mountain community in Pakistan”, Journal of Public Affairs, 2020, doi: https://doi.org/10.1002/pa.2355.

[13] A. D. Dubey, “Twitter Sentiment Analysis during COVID-19 Outbreak,” 2020, doi: https://dx.doi.org/10.2139/ssrn.3572023.

[14] Z. Ceylan, “Estimation of COVID-19 prevalence in Italy, Spain, and France,” Science of the Total Environment, vol. 729, p. 138817, 2020, doi: https://doi.org/10.1016/j.scitotenv.2020.138817.

[15] B. E. Chekol and H. Hagras, “Employing Machine Learning Techniques for the Malaria Epidemic Prediction in Ethiopia,” 2018 10th Computer Science and Electronic Engineering (CEEC), Colchester, United Kingdom, 2018, pp. 89-94, doi: 10.1109/CEEC.2018.8674210.

[16] A. Colubri, M. A. Hartley, M. Siakor, V. Wolfman, A. Felix, T. Sesay, J.G. Shaffer, R.F. Garry, D.S. Grant, A.C. Levine and P. C. Sabeti, “Machine-learning Prognostic Models from the 2014–16 Ebola Outbreak: Data-harmonization Challenges, Validation Strategies, and mHealth Applications,” EClinicalMedicine, vol. 11, 2019, pp. 54-64, doi: https://doi.org/10.1016/j.eclinm.2019.06.003.

[17] F. Petropoulos and S. Makridakis, “Forecasting the novel coro-
navirus COVID-19”, PLoS ONE, vol. 15, no. 3, 2020, doi: https://doi.org/10.1371/journal.pone.0231236.

[18] F. Rustam, A. A. Reshi, A. Mehmood, S. Ullah, B. W. On, W. Aslam and G. S. Choi, “COVID-19 Future Forecasting Using Supervised Machine Learning Models,” in IEEE Access, vol. 8, pp. 101489-101499, 2020, doi: https://doi.org/10.1109/ACCESS.2020.2997311.

[19] T. Chakraborty, and I. Ghosh, “Real-time forecasts and risk assessment of novel coronavirus (COVID-19) cases: A data-driven analysis,” Chaos, Solitons and Fractals, vol. 135, p. 109850, 2020, doi: https://doi.org/10.1016/j.chaos.2020.109850.

[20] D. Kasilingam, S. P. Sathiya Prabhakaran, D. K. Rajendran, V. Rajagopal, T. Santhosh Kumar and A. Soundararaj, “Exploring the growth of COVID-19 using exponential modelling across 42 countries and predicting signs of early containment using machine learning,” Transboundary and Emerging Diseases, pp. 1865-1674, 2020, doi: https://doi.org/10.1111/tbed.13764.

[21] M. Yousaf, S. Zahir, M. Riaz, S. M. Hussain and K. Shah, “Statistical analysis of forecasting COVID-19 for upcoming month in Pakistan,” Chaos, Solitons and Fractals, vol. 138, p. 109926, 2020, doi: https://doi.org/10.1016/j.chaos.2020.109926.

[22] D. W. Hosmer, S. Lemeshow, “Applied logistic regression”, Wiley, New York, 1989.
AUTHOR STATEMENT

Ref: COMPELECENG-D-20-02710

Title: An Intelligent Framework to Predict Socioeconomic Impacts of COVID-19 and Public Sentiments

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Title:
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Conflict of Interest
None Declared.