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ADAPTIVE NEURO FUZZY ESTIMATION OF THE OPTIMAL COVID-19 PREDICTORS FOR GLOBAL TOURISM

Boris Kuzman[1]; Biljana Petković[2]

Abstract

COVID-19 is a pandemic that has emerged as a result of 2019-novel coronavirus droplet infection (2019-nCoV). Recognition of its risk and prognostic factor is critical due to its rapid dissemination and high case-fatality rate. Tourism industry as one of the greatest industries has suffered a lot in the pandemic situation. The main aim of the study was to present travelers' reaction during the pandemic by data mining methodology. The effect of eleven predictors for COVID-19 was also analyzed. The used predictors are: population density, urban population percentage, number of hospital beds, female and male lung size, median age, crime index, population number, smoking index and percentage of females. As the output factors, infection rate, death rate and recovery rate were used. The analyzing procedure was performed by adaptive neuro fuzzy inference system (ANFIS). The results revealed that the frequency of the used words in the pandemic show the highest impact on the travelers' reactions. Number of hospital beds and population number is the optimal combination for the best prediction of infection rate of COVID-19.

Key Words: *COVID-19, Tourism industry, Predictive analytics, Hybrid model, predictors*
JEL classification: *R58, R59*

Introduction

Since December 2019, a novel coronavirus (SARS-CoV-2)-infected pneumonia (COVID-19) has been circulating in Wuhan and has quickly

[1] Boris Kuzman, Professor, Institute of Agricultural Economics, 15 Volgina Street, 11060 Belgrade, Serbia, 063299111
[2] Biljana Petković, Ph.D student, University of Educons, Business Economics, Vojvode Putnika 85-87, 21208 Sremska Kamenica, Serbia, 0655221763

spread throughout China. Predicting the Coronavirus outbreak, which has spread to over 200 countries and has already been declared a pandemic by the World Health Organization, is a difficult challenge. Situational demand is an effective predictor of the unpredictable gruesomeness to ensure better healthcare service management. Demonstrating and forecasting COVID-19 in orders with minimal knowledge structures becomes a difficult task.

In the Wang et al. study, (2020b) it has been suggested that NCD4LR is a potential and useful biomarker for predicting the virus negative conversion time in COVID-19 patients. A hybrid model that incorporates ensemble empirical mode decomposition (EEMD) and artificial neural network (ANN) for predicting the COVID-19 epidemic has been proposed in an article by Hasan (2020) where the result of this investigation showed that the proposed model outperforms compared with traditional statistical analysis. Many laboratory indicators, such as neutrophils, AST, GT, ALP, LDH, NT-proBNP, Hs-cTnT, PT, APTT, D-dimer, IL-2R, IL-6, IL-8, IL-10, TNF, CRP, ferritin and procalcitonin, were all significantly increased in deceased patients compared with recovered patients on admission (Wang et al., 2021a).

In a large cohort of COVID-19 patients of European origin, main risk factors for mortality were older age, comorbidities, low lymphocyte count and high Radiographic Assessment of Lung Edema (RALE) (Fabio et al., 2020). The aim of the research conducted by Xie et al., (2020) was to develop a quantitative method for clinicians to predict the probability of improved prognosis in patients with coronavirus disease 2019 (COVID-19). The impact of obesity on the prognosis and disease severity of COVID-19 has been explored in an article by Tamara & Tahapary (2020) where it was found that obesity is an independent risk and prognostic factor for the disease severity and the requirement of advanced medical care in COVID-19.

Elevated Lactate dehydrogenase (LDH) levels were associated with a ~6-fold increase with regards to developing severe disease and a ~16-fold increase with regards to mortality in patients with COVID-19 (Henry et al., 2020). Totally, 36 clinical indicators significantly associated with severe/critical symptom for COVID-19 were identified (Sun et al., 2020b). Lymphopenia and eosinopenia may serve as predictors of disease severity and disease progression in the COVID-19 patients, and enhancing the cellular immunity may contribute to COVID-19 treatment (Sun et al., 2020a). In a paper by Zhang et al., (2020) a segmented Poisson model was employed to analyze the available daily new cases data of the COVID-19 outbreaks and the analysis allowed to make a statistical prediction on the turning point, the duration and the attack rate.

There are currently no reliable methods for predicting COVID-19's outcome. The main aim of the study was to present travelers' reaction during the pandemic by data mining methodology. It has also established a model for predicting the prognosis of the disease based on the selection of the most impactful predictors. One of the most widely used approaches for modeling and simulation of various structures and processes is artificial neural networks. Since artificial neural networks have parallel architectures for solving complex and highly nonlinear problems, this is the case. Therefore, the main aim of the study is to apply artificial neural network merged with fuzzy logic for analyzing of COVID-19 predictors. The used predictors are: population density, urban population percentage, number of hospital beds, female and male lung size, median age, crime index, population number, smoking index and percentage of females. As the output factors infection rate, death rate and recovery rate were used. Adaptive neuro fuzzy inference system (ANFIS) (Jang, 1993; Laković et al., 2021; Milić et., 2021; Petković et al., 2021a, 2021b, 2021c;) is used as a type of artificial neural network which is suitable for nonlinear data samples.

Methodology

COVID-19 predictors

In order to enable precise and reliable application of the ANFIS methodology there is a need to establish a database with good quality and acceptable size. The data size depends on the data quality. In other words, if the data quality is good then there is no need to increase size of the database. Therefore, the literature review in this study was chosen in order to establish a reliable database.

The TF-IDF is a statistical measure that assesses the relevance of a word to a document in a set of documents. This is accomplished by multiplying two metrics: the number of times a word appears in a document and the word's reciprocal document frequency across a set of documents. The main point is to create a large image of frequently used words. Since the word frequency analysis requires data on individual tokens, even though words have a high frequency, they cannot produce a meaningful big picture. The most commonly repeated words in this study are simple words that also reveal the dataset's thematic structure. When you look at the figure, you'll notice that, PEOPLE, TRAVEL, VIRUS, DAY, CASE, TIME, CANCEL, and TRIP stand out. Any of these terms occur more than 3000 times a year. As a result, even this small number of tokens could mean that the majority of users tend to cancel their trips. The expressions FLIGHT, WEEK, CORONAVIRUS, CHINA, POST, COUNTRY, and GOOD were repeated in the frequency range of 2000–3000.

Table 1 shows input parameters used in the study for covid-19 predictors while Table 2 shows output parameters which are paired with the input data. The used input predictors are: population density (World Population Review, 2021a), urban population percentage (World Population Review, 2021a), number of hospital beds, female and male lung size, median age (World Population Review, 2021b), crime index, population number (Uğur & Akbıyık, 2020), smoking index (Ritchie & Roser, 2013) and percentage of females (The World Bank Group, 2021). As the output factors infection rate, death rate and recovery rate were used (Kaggle, 2020).

Table 1: *COVID-19 predictors*

Country	**Density**	**Urban Population**	**Hospital Bed**	**Lung**	**Female Lung**	**Male Lung**
Albania	105	63	2.9	11.67	7.02	17.04
Algeria	18	73	1.9	8.77	5.03	12.81
Argentina	17	93	5	29.27	20.16	42.59
Armenia	104	63	4.2	23.86	16.17	35.99
Australia	3	86	3.8	18.79	15.9	22.16
Austria	109	57	7.6	17.02	13.02	22.14
Azerbaijan	123	56	4.7	20.61	14.07	29.32
Bahrain	2239	89	6.8	18.37	13.83	22.39
Bangladesh	1265	39	0.8	69.07	61.7	76.24
Belarus	47	79	11	9.46	2.83	21.51
Belgium	383	98	6.2	27.11	21.2	34.98
Bosnia and Herzegovina	64	52	3.5	18.48	12.88	26.05
Brazil	25	88	2.2	26.57	19.71	35.83
Bulgaria	64	76	6.8	19.79	13.98	27.92
Cambodia	95	24	0.8	34.21	30.47	39.66
Canada	4	81	2.7	19.01	16.95	21.55
Chile	26	85	2.2	14.84	12.24	18.58
China	153	61	4.2	63.1	56.35	70.52
Colombia	46	80	1.5	36.3	31.33	42.49

Costa Rica	100	80	1.2	20.42	17.65	23.65
Croatia	73	58	5.6	21.75	14.54	32.7
Cuba	106	78	5.2	23.3	20.53	26.67
Cyprus	131	67	3.4	17.85	11.34	26.04
Czech Republic	139	74	6.5	19.68	13.1	28.54
Denmark	137	88	2.5	31.99	31.31	32.85
Dominican Republic	225	85	1.6	11.43	9.5	13.57
Ecuador	71	63	1.5	24.07	18.85	30.17
Estonia	31	68	5	8.8	3.59	18.36
Ethiopia	115	21	0.3	18.56	13.55	24.28
Finland	18	86	4.4	9.92	5.47	15.97
France	119	82	6.5	13.15	9.64	17.69
Georgia	57	58	2.6	23.26	15.96	34.46
Germany	240	76	8.3	20.01	16.32	24.67
Ghana	137	57	0.9	21.09	17.95	25.11
Greece	81	85	4.3	20.62	18.3	23.49
Honduras	89	57	0.7	21.39	22.03	20.76
Hungary	107	72	7	27.68	19.86	39.93
Iceland	3	94	3.2	19.71	20.44	18.65
India	464	35	0.7	96.92	87.54	106.89
Indonesia	151	56	1.2	36.26	23.54	51.83
Ireland	72	63	2.8	24.92	23.02	27.25
Israel	400	93	3.1	16.1	12.81	20.23
Italy	206	69	3.4	17	12.78	22.78
Jamaica	273	55	1.7	15.74	6.33	26.44
Japan	347	92	13.4	12.17	5.8	20.85
Kazakhstan	7	58	6.7	114.28	79.27	174.88
Kenya	94	28	1.4	19.15	14.92	24.16
South Korea	527	82	11.5	10.48	6.6	16.23
Kuwait	240	92	2	10.99	7.44	13.43
Latvia	30	69	5.8	8.06	2.76	17.68
Lebanon	667	78	2.9	17.28	13.86	20.78
Lithuania	43	71	7.3	11.5	4.13	25.02
Luxembourg	242	88	4.8	20.52	17.2	24.91
Malaysia	99	78	1.9	23.73	12.95	34.24
Maldives	1802	35	4.3	26.7	26.61	26.89
Malta	1380	93	4.7	12.05	6.66	19.15
Mauritius	626	41	3.4	30.56	17.36	48.62
Mexico	66	84	1.5	27.85	23.43	33.14
Moldova	123	43	5.8	17.13	9.21	29.88
Mongolia	2	67	7	13.4	9.3	18.76
Montenegro	47	68	4	17.6	10.7	26.47

Morocco	83	64	1.1	10.39	7.51	13.73
Namibia	3	55	2.7	43.86	29.39	65.58
Nepal	203	21	0.3	100.75	94.59	107.64
Netherlands	508	92	4.7	26	22.74	30.36
New Zealand	18	87	2.8	21.88	19.66	24.61
Nigeria	226	52	0.3	21.14	19.65	22.75
Norway	15	83	3.9	26.13	23.51	29.49
Oman	16	87	1.6	10.87	9.06	12.54
Pakistan	287	35	0.6	50.61	35.5	64.92
Panama	58	68	2.3	24.25	19.96	29.06
Peru	26	79	1.6	17.69	14.94	20.96
Philippines	368	47	1	44.52	27.04	67.56
Poland	124	60	6.5	16.16	9.98	25.9
Portugal	111	66	3.4	13.35	9.14	19.18
Qatar	248	96	1.2	7.87	5.37	9.21
Romania	84	55	6.3	18.8	10.65	30.05
Saudi Arabia	16	84	2.7	12.41	9.55	15.56
Serbia	100	56	5.7	23.27	15.49	33.82
Singapore	8358	99	2.4	8.32	3.17	14.81
Slovenia	103	55	4.6	11.89	8.36	16.95
South Africa	49	67	2.8	44.3	28.03	75.32
Spain	94	80	3	16.37	8.22	27.49
Sri Lanka	341	18	3.6	21.58	15.38	29.36
Sweden	25	88	2.6	16.17	16.58	17.03
Switzerland	219	74	4.7	15.22	11.94	19.47
Tanzania	67	37	0.7	18.09	14.24	22.47
Thailand	137	51	2.1	25.82	12.91	41.67
Tunisia	76	70	2.3	23.54	10.97	38.83
Turkey	110	76	2.7	35.63	21.2	55.26
United States	36	83	2.9	32.01	30.04	34.55
Ukraine	75	69	8.8	11.11	4.73	22.11
United Arab Emirates	118	86	1.2	18.37	12.55	20.21
United Kingdom	281	83	2.8	23.66	21.11	26.84
Uruguay	20	96	2.8	33.57	23.14	49.85
Vietnam	314	38	2.6	26.26	16.8	41.72

Country	**Median Age**	**Crime Index**	**Population 2020**	**Smoking 2016**	**Females 2018**
Albania	32.9	40.02	2877.797	28.7	49.06309
Algeria	28.1	54.41	43851.04	15.6	49.48427
Argentina	31.7	62.96	45195.77	21.8	51.23735
Armenia	35.1	20.78	2963.243	24.1	52.95658
Australia	38.7	42.7	25499.88	14.7	50.19962

Austria	44	23.23	9006.398	29.6	50.82943
Azerbaijan	31.3	32.68	10139.18	20.8	50.11575
Bahrain	32.3	29.18	1701.575	26.4	36.34825
Bangladesh	26.7	64.98	164689.4	23	49.3873
Belarus	40	24.8	9449.323	26.7	53.45605
Belgium	41.4	42.5	11589.62	28.2	50.59332
Bosnia and Herzegovina	42.1	43.57	3280.819	38.9	51.01054
Brazil	32	69.48	212559.4	13.9	50.82992
Bulgaria	42.7	39.31	6948.445	37	51.41409
Cambodia	25.3	51.8	16718.97	17.2	51.19798
Canada	42.2	39.48	37742.15	14.3	50.39153
Chile	34.4	47.12	19116.2	37.8	50.72703
China	37.4	36.7	1439324	25.6	48.67937
Colombia	30	52.54	50882.89	9	50.92577
Costa Rica	31.3	55.77	5094.118	11.9	50.00985
Croatia	43	24.23	4105.267	37	51.85262
Cuba	41.5	27.62	11326.62	35.2	50.33285
Cyprus	36.8	29.62	1207.359	36.4	49.97107
Czech Republic	42.1	25.99	10708.98	34.3	50.80859
Denmark	42.2	24.72	5792.202	19.1	50.2742
Dominican Republic	28.1	60.62	10847.91	13.7	50.0078
Ecuador	27.7	48.91	17643.05	7.1	49.97063
Estonia	42.7	22.17	1326.535	31.3	52.85843
Ethiopia	17.9	47.46	114963.6	4.4	49.97889
Finland	42.5	22.75	5540.72	20.4	50.72076
France	41.4	46.45	65273.51	32.7	51.58424
Georgia	38.1	20.18	3989.167	28.8	52.29124
Germany	47.1	34.6	83783.94	30.6	50.66037
Ghana	21.1	51.57	31072.94	3.9	49.32583
Greece	44.5	39.29	10423.05	43.4	50.9162
Honduras	23	75.84	9904.607	2	50.04934
Hungary	42.3	35.41	9660.351	30.6	52.43243
Iceland	36.5	23.15	341.243	14.7	49.81171
India	27.9	42.38	1380004	11.5	48.02354
Indonesia	30.2	46.26	273523.6	39.4	49.64388
Ireland	36.8	46.18	4937.786	24.3	50.42551
Israel	29.9	30.71	8655.535	25.2	50.29813
Italy	45.5	44.35	60461.83	23.7	51.37667
Jamaica	26	65.26	2961.167	16.8	50.33983
Japan	47.3	15.91	126476.5	22.1	51.15926
Kazakhstan	30.6	64.23	18776.71	24	51.51148

Kenya	19.7	62.38	53771.3	10.7	50.31602
South Korea	41.8	29.24	51269.19	23.3	49.91688
Kuwait	29.3	35.61	4270.571	22.5	39.54817
Latvia	43.6	36.6	1886.198	37	54.01017
Lebanon	30.5	43.38	6825.445	33.8	49.70581
Lithuania	43.7	34.82	2722.289	28.8	53.79196
Luxembourg	39.3	30.17	625.978	23.5	49.53926
Malaysia	28.5	60.66	32366	21.5	48.57852
Maldives	28.2	53.83	540.544	28.3	37.26498
Malta	41.8	37.73	441.543	25.5	49.87331
Mauritius	35.3	47.34	1271.768	21.6	50.57711
Mexico	28.3	52.51	128932.8	14	51.08928
Moldova	36.7	45.7	4033.963	24.2	52.03556
Mongolia	28.3	57.76	3278.29	25.6	50.66954
Montenegro	40.7	39.67	628.066	45.9	50.55901
Morocco	29.3	49.53	36910.56	23.4	50.40385
Namibia	21.2	68.14	2540.905	21.4	51.55369
Nepal	24.1	35.7	29136.81	22.8	54.53534
Netherlands	42.6	28.54	17134.87	25.8	50.22094
New Zealand	37.9	40.89	4822.233	16	50.83777
Nigeria	18.4	64.64	206139.6	5.8	49.33611
Norway	39.2	33.51	5421.241	20.2	49.52463
Oman	25.6	21.55	5106.626	11.1	34.01408
Pakistan	23.8	44.58	220892.3	20.1	48.53807
Panama	29.2	45.47	4314.767	6.1	49.90538
Peru	28	64.58	32971.85	4.8	50.33776
Philippines	23.5	41.09	109581.1	24.3	49.74166
Poland	40.7	29.67	37846.61	28	51.53071
Portugal	42.2	30.11	10196.71	22.7	52.71196
Qatar	33.2	12	2881.053	20.6	24.49529
Romania	41.1	27.84	19237.69	29.7	51.34374
Saudi Arabia	27.5	28.22	34813.87	15.6	42.44585
Serbia	42.6	37.63	8737.371	38.9	51.00252
Singapore	34.6	27.7	5850.342	16.5	47.65813
Slovenia	44.5	22.01	2078.938	22.5	50.24521
South Africa	27.1	77.02	59308.69	20.3	50.69415
Spain	42.7	31.07	46754.78	29.3	50.89664
Sri Lanka	32.8	40.15	21413.25	13	51.96682
Sweden	41.2	47.21	10099.27	18.8	49.94578
Switzerland	42.4	21.18	8654.622	25.7	50.42712
Tanzania	17.7	59.83	59734.22	14.8	50.05101
Thailand	37.7	41.29	69799.98	19.9	51.2687
Tunisia	31.6	40.64	11818.62	32.7	50.43715

Turkey	30.9	39.86	84339.07	27.2	50.67781
United States	38.1	46.73	331002.7	21.8	50.52001
Ukraine	40.6	49.04	43733.76	28.9	53.68775
United Arab Emirates	30.3	15.52	9890.402	28.9	30.63669
United Kingdom	40.5	43.64	67886.01	22.3	50.63527
Uruguay	35	52.33	3473.73	16.8	51.72154
Vietnam	30.5	48.22	97338.58	22.8	50.09641

Source: *Kaggle (2020)*

Table 2: *Output parameters for COVID-19*

Country	**Total Infected**	**Total Deaths**	**Total Recovered**	**Country**	**Total Infected**	**Total Deaths**	**Total Recovered**
Albania	949	31	742	Kuwait	16764	121	4681
Algeria	7377	561	3746	Latvia	1012	21	694
Argentina	8809	393	2872	Lebanon	954	26	251
Armenia	5041	64	2164	Lithuania	1562	60	1025
Australia	7072	100	6431	Luxembourg	3958	109	3718
Austria	16321	632	14678	Malaysia	6978	114	5646
Azerbaijan	3518	41	2198	Maldives	1143	4	91
Bahrain	7532	12	2952	Malta	569	6	460
Bangladesh	25121	370	4993	Mauritius	332	10	322
Belarus	31508	175	10620	Mexico	54346	5666	37325
Belgium	55791	9108	14687	Moldova	6340	221	2508
Bosnia and Herzegovina	2321	134	1522	Mongolia	140	0	26
Brazil	271885	17983	106794	Montenegro	324	9	312
Bulgaria	2259	112	646	Morocco	7023	193	3901
Cambodia	122	0	122	Namibia	16	0	13
Canada	80493	6028	40069	Nepal	402	2	37
Chile	49579	509	21507	Netherlands	44449	5734	167
China	84063	4638	79310	New Zealand	1503	21	1447
Colombia	16935	613	4050	Nigeria	6401	192	1734
Costa Rica	882	10	577	Norway	8267	233	32
Croatia	2232	96	1967	Oman	5671	27	1574
Cuba	1887	79	1538	Pakistan	43966	939	12489
Cyprus	918	17	515	Panama	9867	281	6194
Czech Republic	8647	302	5726	Peru	99483	2914	36524
Denmark	11242	551	9614	Philippines	12942	837	2843
Dominican Republic	13223	441	6613	Poland	19268	948	7903
Ecuador	34151	2839	3457	Portugal	29432	1247	6431

Estonia	1791	64	938	Qatar	35606	15	5634
Ethiopia	365	5	120	Romania	17191	1137	10166
Finland	6399	301	5000	Saudi Arabia	59854	329	31634
France	180933	28025	62678	Serbia	10733	234	4904
Georgia	707	12	456	Singapore	28794	22	10365
Germany	177778	8081	155681	Slovenia	1467	104	1338
Ghana	6096	31	1773	South Africa	17200	312	7960
Greece	2840	165	1374	Spain	232037	27778	0
Honduras	2955	147	349	Sri Lanka	1027	9	569
Hungary	3556	467	1412	Sweden	30799	3743	4971
Iceland	1802	10	1789	Switzerland	30618	1891	27700
India	106475	3302	42309	Tanzania	509	21	183
Indonesia	18496	1221	4467	Thailand	3033	56	2857
Ireland	24251	1561	19470	Tunisia	1044	47	826
Israel	16659	278	13435	Turkey	151615	4199	112895
Italy	226699	32169	129401	United States	1528568	91921	289392
Jamaica	520	9	145	Ukraine	18876	548	5632
Japan	16367	768	11564	United Arab Emirates	25063	227	10791
Kazakhstan	6751	35	3598	United Kingdom	250138	35422	1099
Kenya	963	50	358	Uruguay	738	20	579
South Korea	11110	263	10066	Vietnam	324	0	263

Source: *Kaggle (2020)*

ANFIS methodology

ANFIS network is shown in Figure 1 where five layers can be observed. Fuzzy inference system is the main core of the network. The main principle of the network is to include input and output data samples and to train the network.

Figure 1: *ANFIS*

Source: *Jang (1993)*

Results

The most influential variables for the TF-IDF were chosen using the ANFIS methodology. The selection is crucial, as is the preprocessing of the input parameters to exclude irrelevant inputs. The data collection is organized based on Table 1's data file. Following the commands in MATLAB Software, the dataset is partitioned into a training set (odd-indexed samples) and a checking set (even-indexed samples):

```
[data] = TF-IDF;
trn_data = data(1:2:end,:);
chk_data = data(2:2:end,:);
```

The function "exhsrch" conducts an exhaustive search of the available inputs to identify the collection of inputs that have the greatest effect on the TF-IDF. The function's first parameter determines the number of input combinations that will be tested during the selection process. In essence, "exhsrch" creates an ANFIS model for each combination, trains it for one epoch, and then reports the results. The command line below is used to evaluate the single most important attribute in predicting the outcome:

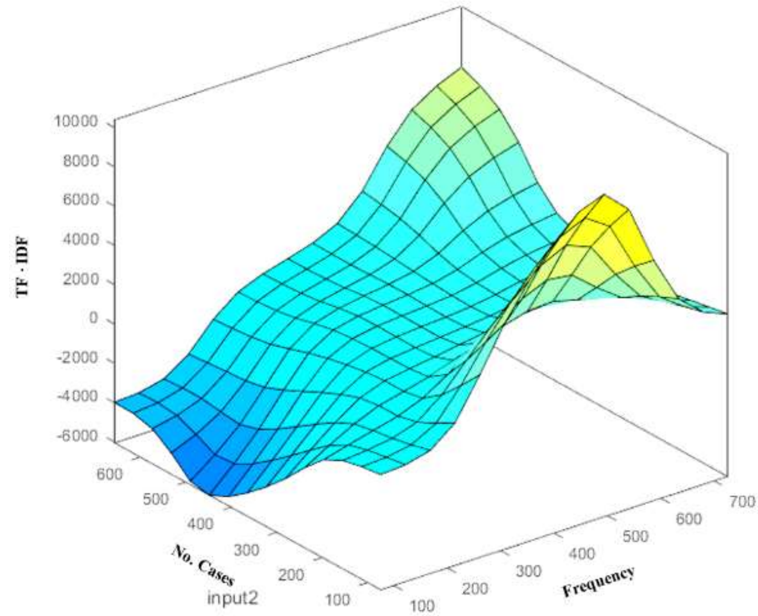
```
exhsrch(1,trn_data,chk_data);
```

The following results are obtained

```
ANFIS model 1: in1 --> trn=4.7729, chk=4.0893
ANFIS model 2: in2 --> trn=20.3109, chk=16.3539
ANFIS model 3: in3 --> trn=20.2467, chk=15.9928
```

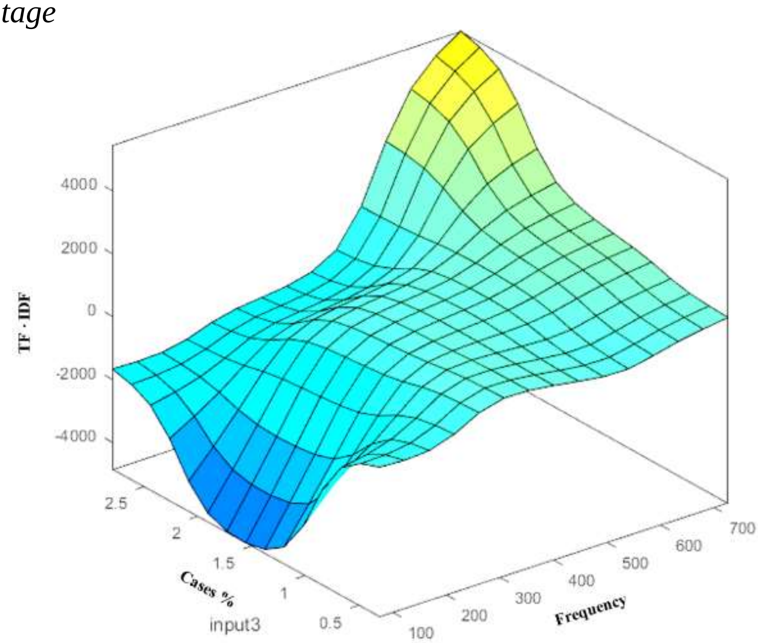
In terms of the output, the input variable 1 has the least error, or in other words, the most significance. The results show that the input attribute "Frequency" has the greatest impact on the TF-IDF. There is no overfitting since the preparation and checking errors are equivalent. The ANFIS decision surfaces for TF-IDF based on the three factors are shown in Figures 2-4.

Figure 2: *ANFIS prediction of TF-IDF based on frequency and number of cases*



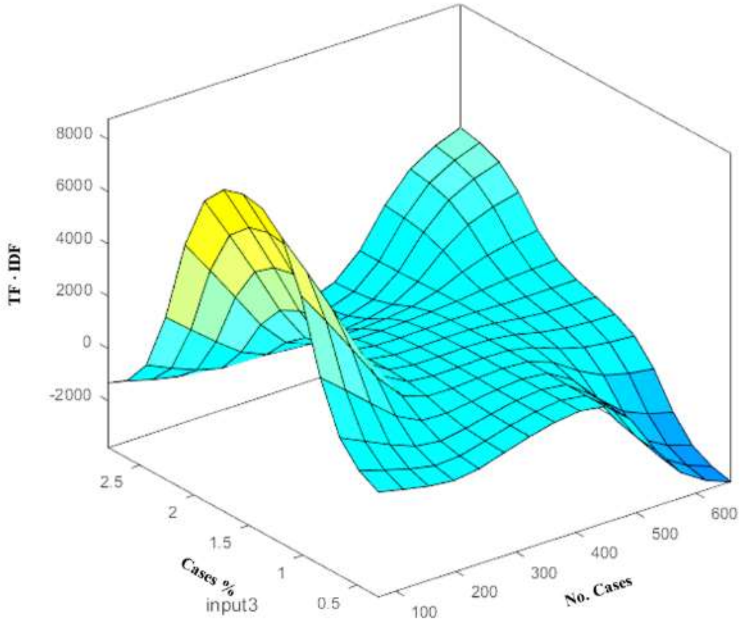
Source: *Authors' own work*

Figure 3: *ANFIS prediction of TF-IDF based on frequency and cases percentage*



Source: *Authors' own work*

Figure 4: *ANFIS prediction of TF-IDF based on number of cases and cases percentage*



Source: *Authors' own work*

COVID-19 predictors selection

According to training error (trn) in Table 3 population number in 2020 (bold value) has the strongest impact on infection rate. Checking (chk) error is used for tracking of overfitting between training and checking data. The same observations can be noted in Tables 4 and 5 for death rate and recovery rate prediction. Therefore number of population is the strongest single predictor for COVID-19.

Table 3: *COVID-19 predictors' accuracy for infection rate*

ANFIS model 1: Density --> trn=221712.2483, chk=173428.0136
ANFIS model 2: Urban Population --> trn=217111.7985, chk=79355.5141
ANFIS model 3: Hospital Bed --> trn=222877.0509, chk=59218.0037
ANFIS model 4: Lung --> trn=219926.4973, chk=71736.6272
ANFIS model 5: Female Lung --> trn=217976.8181, chk=63537.7839
ANFIS model 6: Male Lung --> trn=220320.5213, chk=118569.4758
ANFIS model 7: Median Age --> trn=218230.4643, chk=78625.0855
ANFIS model 8: Crime Index --> trn=220665.8308, chk=60387.4698

ANFIS model 9: Population 2020 --> trn=82662.2518, chk=436987.4859
ANFIS model 10: Smoking 2016 --> trn=220159.9990, chk=72984.8979
ANFIS model 11: Females 2018 --> trn=222482.2861, chk=65735.7301

Source: *Authors' own work*

Table 4: *COVID-19 predictors' accuracy for death rate*

ANFIS model 1: Density --> trn=14616.7168, chk=7129.0294
ANFIS model 2: Urban Population --> trn=14098.2589, chk=7508.5184
ANFIS model 3: Hospital Bed --> trn=14625.7927, chk=6237.5719
ANFIS model 4: Lung --> trn=14595.9762, chk=6070.9450
ANFIS model 5: Female Lung --> trn=14539.0685, chk=5715.5738
ANFIS model 6: Male Lung --> trn=14546.6911, chk=7819.8976
ANFIS model 7: Median Age --> trn=14194.7566, chk=7082.8291
ANFIS model 8: Crime Index --> trn=14476.0085, chk=5897.0950
ANFIS model 9: Population 2020 --> trn=8314.3409, chk=25039.1436
ANFIS model 10: Smoking 2016 --> trn=14442.2460, chk=6845.0943
ANFIS model 11: Females 2018 --> trn=14573.2227, chk=7057.1682

Source: *Authors' own work*

Table 5: *COVID-19 predictors' accuracy for recovery rate*

ANFIS model 1: Density --> trn=50722.7634, chk=24905.3444
ANFIS model 2: Urban Population --> trn=48831.7813, chk=26000.0839
ANFIS model 3: Hospital Bed --> trn=50058.7364, chk=29588.6144
ANFIS model 4: Lung --> trn=50372.4841, chk=27090.3174
ANFIS model 5: Female Lung --> trn=50056.1160, chk=23182.5764
ANFIS model 6: Male Lung --> trn=50307.3893, chk=38889.7417
ANFIS model 7: Median Age --> trn=49433.9358, chk=25140.0393
ANFIS model 8: Crime Index --> trn=50382.1178, chk=22497.1108
ANFIS model 9: Population 2020 --> trn=31874.6665, chk=74489.6323
ANFIS model 10: Smoking 2016 --> trn=50280.8124, chk=23877.6985
ANFIS model 11: Females 2018 --> trn=50654.2781, chk=24425.0319

Source: *Authors' own work*

Conclusion

The infection of Coronavirus Disease 2019 (COVID-19) has now spread worldwide, affecting over a million people. To reduce morbidity and social burden, predictors of disease outcomes in these patients must be evaluated as soon as possible.

In this study, the effect of eleven predictors for COVID-19 was analyzed. The main concluding remarks are:

- The combination of number of hospital beds, population number and smoking index is the optimal combination for the best prediction of infection rate of COVID-19.
- The optimal combination of the predictors for the death rate is number of hospital beds, median age and population number.
- The combination of median age, crime index and population number is the most impactful combination for the death rate of COVID-19.

The results revealing the frequency of the used words in the pandemic show the highest impact on the travelers' reactions. The travel industry was already having problems. Many businesses have mastered the complexities of digitization and thrived in a rapidly evolving world. The scale of Covid-19's effects, on the other hand, is not comparable to previous crises. The demand for mobility, consumption, and independence is expected to remain strong in the future, but it will be shaped by local considerations.

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