Employing Machine Learning for Predicting Transportation Modes under the COVID-19 Pandemic: A Mobility-Trends Analysis

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***Abstract*—With the advent of Coronavirus Disease 2019 (COVID-19), the world encountered an unprecedented health crisis due to the severe acute respiratory syndrome (SARS) pathogen. This impacted all of the sectors but more critically the transportation sector which required a strategy in the light of mobility trends using transportation modes and regions. We analyse a mobility prediction model for smart transportation by considering key indicators including data selection, processing and, integration of transportation modes, and data point normalisation in regional mobility. A Machine Learning (ML) driven classification has been performed to predict transportation modes efficiency and variations using driving, walking and transit. Additionally, regional mobility by considering Asia, Europe, Africa, Australasia, Middle-East, and America has also been analysed. In this regard, six ML algorithms have been applied for the precise assessment of transportation modes and regions. The initial experimental results demonstrate that the majority of the world's travelling dynamics have been contrastively shaped with the accuracy of 91.21% and 84.5% using Support Vector Machine (SVM) and Random Forest (RT) for different transportation modes and regions. This study will pave a new direction for the assessment of transportation modes affected by the pandemic to optimize economic benefits for smart transportation.**

***Index Terms*—Artificial Intelligence, COVID-19, Intelligent Transport Systems, Mobility Management, Travelers-Tracing.**

I. Introduction

The COVID-19 pandemic has impacted all aspects of social life dimensions ranging from medical, business, transportation, environment, governance, and planning. Due to the enforced restrictions to control the virus spread worldwide, local governments took safety measures resulting in limited mass transportation [1]. Different transport modes including, but not limited to, air, rail, road, and water have all been affected. In addition, freight services have also been severely affected due to the complicated supply and demand trends. Due to the SARS health crisis, the transportation sector adversely impacted which became the main cause to unpredictably shaped the 2020 mobility index. The aviation industry activities dropped by 62%, rail travel decreased to 60% while car transport had a decrease in travel by almost 60% since March 2020 [2], [3]. By end of October 2020, regions such as Asia, Europe, Africa, Australasia, Middle-East and America were almost 50% below the 2019 average according to the mobility index figures [4]. While Europe and America are the biggest supporters of keeping the economy and businesses shut until COVID-19 was fully contained. Asia and Australasia find it vital to restart the economy regardless. The rail travel decreased to just 5% of pre-pandemic levels during the lockdown in late March and April 2020. Numbers are still only at 30%-40% of those in 2019 due to travel restrictions [5], [6].

The decline in transportation in Europe according to the UK statistics, the government spent up to £3.5bn covering train companies' losses since the pandemic began. Under the existing system, companies tender to run services on routes on multiyear agreements. The rail operatives then made payments to the state based on ticket revenue estimates, but the pandemic destroyed that business model and culture affecting the mobility trend [7]. In Asia, according to China's National Bureau of Statistics, the oil refinery and trade production in February 2020 indicate a slump in total oil demand with over 20% comparable to February 2019 [8]. This backdrop recession in the energy market impacted mobility trend in all transport modes. Furthermore, the overall energy requirement of Canada for the month of April 2020 declined by 14% amidst pandemic conditions [9]. In particular, passenger transport is responsible for 15% of global energy-related carbon emissions and almost 40% of final oil demand [7], [10]. In Americas according to the statistics recorded by the Canadian government, the transportation sector accounted for 30% of the total energy demand which is fossil-based with substantial environmental impacts[1]. In Africa according to the statistics recorded by International Air Transport Association (IATA), the projected revenue losses of up to US$113 billion and the United Nations Economic Commission for Africa (UNECA) estimated at least US$65 billion in revenue losses among Africa's top 10 fuel exporting economies. Moreover, due to COVID-19 disruptions

[1]https://www.canada.ca/content/dam/eccc/documents/pdf/cesindicators/ghg-emissions/2019/national-GHG-emissions-en.pdf

in global value chains among other things, the World Trade Organization (WTO) projected a decline in world trade of between 13% and 32% in 2020. Overall, an unprecedented global recession is being envisaged with a world GDP slump ranging between 0.5% and 3.8%[2]. In Australasia, a reduction in economy-wide productivity of capital of -0.57% (a third of the reduction in labour) due to the breakdown in global supply chains. Government spending increased by 1% on health, transport, and public. International trading suffered an increment of only 1% when supply chains are integrated across borders. A 5% increase in costs that move goods and people (trade, air transport), tourism, education and recreation with the estimated pandemic-related contraction of 1.32% GDP[3].

Hence, the mobility trends due to COVID-19 will result in significant mobility changes for which predicting the future transport modes and associated data realisation is necessary for any interface running applications. When mobility disruptions are concerned, on the contrary, it benefits travellers to adapt to more sustainable transportation modes with precautionary measures [9]. COVID-19 indirect impacts include revenue generation in line with the manufacturing capacity and foreign investments. The Pearson correlation is -0.496 (approximately 43% reduction) between pandemic and the exports whereas -0.873 is the normal growth figure [8].

Will the global crisis under COVID-19 pandemic result in long-lasting reductions, conserved user mobility, and behavioral changes in transport demand? To the authors' knowledge, this issue has not been investigated before, and the appropriate definition and prediction of regional transport and its correlation with multiple mobility modes (e.g. driving, walking, and transit trips) could avoid a slowdown in spreading the infection and hence forming a smart transport network with restrictive and mitigative measures. Related ML works in terms of users mobility predictions have been completed in [1], [10], [11], [14] to address multiple mobility challenges such as users mobility profiling, base stations switching on/off operation by considering users mobility, train traffic flows and encryption, and mobility management to address energy affected issues by using ML. The main contribution of this study lies in the employing ML for predicting transportation modes under the pandemic and analysing future mobility trends. The observed mobility data is pre-processed and put into proposed ML algorithm. Thus, the integration of ML algorithms have demonstrated the strong potential of evaluating different transportation modes and regions. With this modelled dataset, it provides an opportunity to the researchers to extend the topic in light with our study to address global transportation needs, significant energy savings, carbon emissions, development of smart transportation modes, etc [10]. Due to the uniqueness of this paper's approach, we believe that our analysis will steer the direction of researchers in comprehending the magnitude of mobility trends and its impact on transportation needs.

[2]https://unctad.org/system/files/official-document/aldcmisc2020d3_en.pdf

[3]https://www.pwc.com.au/publications/australia-matters/economic-consequences-coronavirus-COVID-19-pandemic.pdf

Therefore, we have contributed to the objectives as follows:

- Global transportation analysis and conserved mobility in light of COVID-19.
- Assessing the mobility trends by using Machine Learning (ML) classification predictions.
- Predicting behavioural changes of daily travellers stemming from COVID-19 and exploration of long-term shifts in transportation modes.

Fig. 1. World-wide regional mobility impact on the transportation modes due to COVID-19 pandemic.

II. System Model and Data Generation

The modelling of global different transportation modes and the impacts of COVID-19 has been shown in Fig. 1. We present the model to assess the transportation sector using following indicators [9], [11], [12] forming a smart transport network.

$$\Gamma_{(d,s,w)}(t) = \beta_i \; \tau(t) \; \alpha_{(d,s,w)}(t) \tag{1}$$

This domain is explored by assessing a number of indicators including efficient data selection and integration of transportation modes β_i where $\beta_i \in (d = driving, s = transit, w = walking)$, regional mobility $\alpha_{(d,s,w)}(t)$, and data points normalisation through traffic arrival rate $\tau(t) = \gamma_r/\gamma_f$. The $\tau(t)$ is the rate at which data gets recorded for all the transportation modes, γ_r is the amount of time impacted by COVID-19 in a region while γ_f is the baseline of travel times unaffected from any conditions across each transportation segment in each region. Fig. 2 shows the framework development of functional indicators. The presented model would exploit all the opportunities to a specific niche while choosing different parameters. Our objective lies in predicting the transportation modes under COVID-19 pandemic while analysing the mobility trends contributing to smart transportation from a comprehensive and holistic approach.

A. Data Selection, Processing and Integration

A granular-level of data has been collected for different transportation modes in six regions. This data selection was completed by individually mining driving, transit and walking modes of transportation in the world. Initially the used data

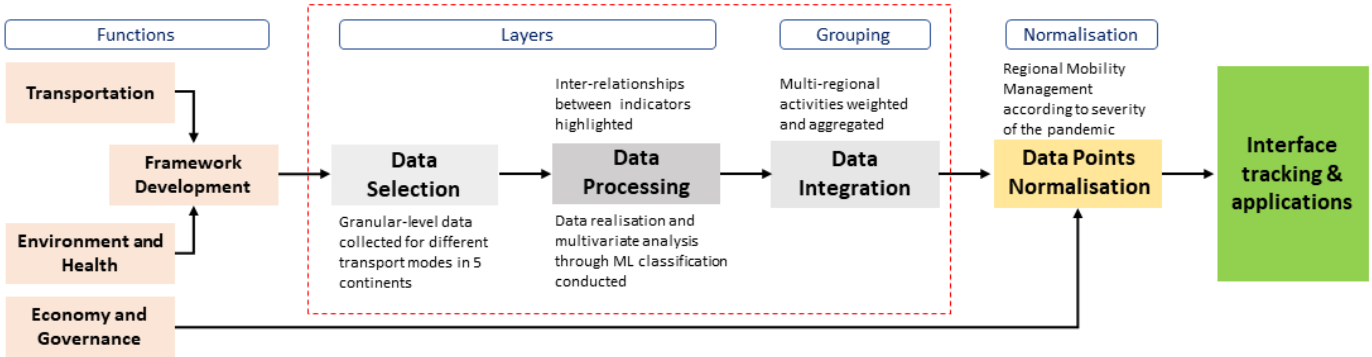


Fig. 2. Smart transportation assessment methodology flow diagram.

was available in such a way that cities, countries, provinces, and states were shown in a detailed fashion along with daily mobility. It was difficult to sequentially formulate such a huge dataset into one suitable file for ML processing, thus data averaging was performed to assist any past random fluctuation to exploit the central trend of the data set. Such approach is aligned with [10], [11], [12], [13] which highlight the importance of collecting complex data, supporting research design vulnerabilities to validate challenges, and building in necessary longitudinal elements. The integration of transport modes is critical to the prosperity of any region as well as the enhancements of the mobility sector. This indicator focuses on the different modes of transportation i.e driving, transit and walking, affected by the pandemic. In this instance, by using artificial intelligence (AI), close monitoring of mobility trends are possible to further develop advancements in the field of smart transport modes. We assessed this indicator as a ratio of advanced technology used in transport modes to the area of the region as;

$$\beta_i(d|s|w \subseteq D) = \left[\sum_{d=1}^{\alpha_d^t} \frac{\beta_d}{A_d} + \sum_{s=1}^{\alpha_s^t} \frac{\beta_s}{A_s} + \sum_{w=1}^{\alpha_w^t} \frac{\beta_w}{A_w} \right] \tag{2}$$

where, β_i denotes the integration of all the transport modes obtained from dataset D. Driving β_d, transit β_s, and walking β_w represent individual modes based on their regional areas defined as A. Each transport mode has a range limit as $(1 \rightarrow \alpha)$ where α being the regional mobility to accommodate travelers in a given time t.

B. Data Points Normalisation in Regional Mobility

Data points with the density and management of traffic in a particular region have been normalised to predict mobility trends through traffic arrival rate which is one of a critical parameters that need to be monitored for efficient mobility trends and smooth flows of traffic. We have baselined the different modes, dates, times, and regions of travel across each transportation segment. Travel times from the start of COVID-19 for each region are analysed and compared against free flow periods to derive the data points normalisation through traffic arrival rate $\tau(t)$. Regional mobility in transport planning driven by a concept of smart transportation refers to a measure of smooth flow of traffic and easy movement while reaching destinations or activities throughout the regions [12], [14], [15]. We have used regional mobility index to quantify accessibility for each region such as Asia, Europe, Africa, Australasia, Middle-East and America. The following function assesses this indicator:

$$\alpha_{(d,s,w)}(t) = \frac{\sum_{x=1}^{\infty} \mathbb{R}}{d} \tag{3}$$

where, $\sum \mathbb{R}$ represents the total length of the accessible routes in (km) to the total length of the transportation system d in any given region.

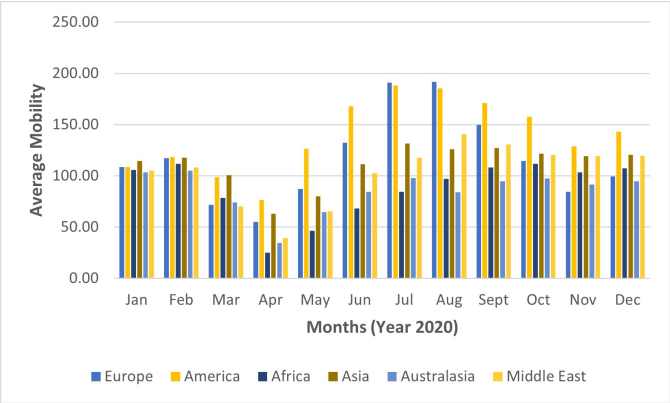
III. Results And Discussion

Due to the magnitude of globally impacted COVID-19 crisis, the consequent impacts are also exceptional. Global mobility took a new trend since the pandemic which restricted all the modes of transportation. The restrictions were imposed by authorities throughout the world affecting people's lives and behaviors[4]. In the following subsections, we first present the simulation results of mobility trends using different modes of transportation and regions which is shown in Fig. 3. Due to the extensive size of the dataset, we have chosen few indicators out of many such as months, modes, regions, etc. The results shown the mobility trends are simulated by comparing trips planned to a recent typical usage period by averaging the values. We also discuss and present results obtained from ML-driven classifiers as shown in Tables I and II.

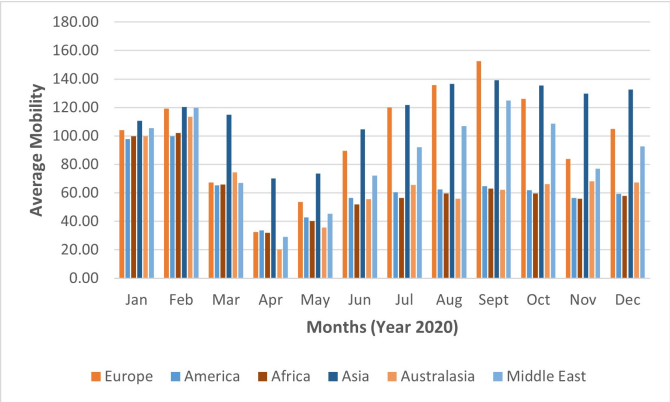
A. Realisation of Dataset and Analysis

Prior to the pandemic the average world-wide mobility was not heavily affected which can be seen in January and February 2020 figures, however, it dropped from its normal operational level[5]. Whereas, observed numbers from China and Japan reduced to almost 50% followed by the rest of the world reduced mobility numbers when the wave triggered at the start of March 2020. During this time, many juridictions were put in place to abruptly stop public transport and other means

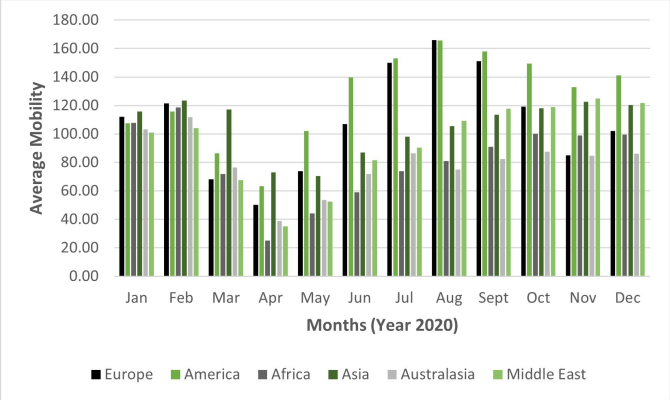
[4]Citymapper Mobility Index. https://citymapper.com
[5]IATA Economics' Chart of the Week, Report 2020.



(a) Driving Mobility Trend.



(b) Transit Mobility Trend.



(c) Walking Mobility Trend.

Fig. 3. Simulation results for global mobility trends in response to COVID-19 pandemic. Plotted trends outline the different modes of transport and regions. Out of large dataset, results are averaged and combined for clarity.

of non-essential transportation. This had an effect on severe declination in the mobility index to unprecedented low levels. From March to May 2020, mobility either driving, transit, or walking was virtually non-existent until the restrictions were relaxed with extra precautions from June to October 2020 which is shown in Fig. 3. In driving mobility trend, the worst case was observed in April 2020 world-wide which was almost 30% compared to January 2020 figures. Best figures were observed in July, August, and September 2020 which were approximately 50% to 70% more than January 2020. This means the transportation was revived after restrictions were lifted. In transit and walking, similar mobility trends were observed. Unlike other regions trend-line, it is also observed that Europe's average mobility trend through driving, transit, and walking was considerably high.

B. ML-driven Mobility Prediction Classification

The presented ML-driven mobility classification analyses evaluation metrics which are used to predict mobility trends according to the different modes of transportation and regions in the world. ML is used in the assortment of pattern recognition and mobility traces to establish automation in intelligent decisions while learning from history and adapt to the testing environment [14], [15]. The modelled tracking will provide an opportunity to the researchers to take necessary actions for extending the topic. Actions such as monitoring mobility trends for the use of specific industry, admission control for the daily commuters to a specific field of profession, advising daily travelers to take certain safe mobility pathways/routes, tracing and safeguarding any vulnerabilities, etc [1], [11]. For evaluating the performance of the approach, $scikit-learn$ Python libraries are used to implement six ML algorithms along with six classifiers such as, the accuracy, precision, recall, and F-measure. The summary of the results are shown in Tables I and II. SVM classifier outperforms among others in predicting different transportation modes with default RBF kernel parameters settings with kernel size 200 whereas RT presented best results for assessing the different regions. The main reason for the SVM performance in Table I compared to other algorithms is SVM's more effectiveness in high dimensional spaces and relatively more memory efficient. However, in order to train the ML algorithms the raw data has been used to train the model. Table II shows that RT algorithm achieved higher performance among all others. It is worth to mention that the RT reduces overfitting in decision trees and helps to improve the accuracy.

TABLE I
MOBILITY PREDICTION CLASSIFICATION FOR DIFFERENT TRANSPORTATION MODES ACROSS THE WORLD

Machine Learning Classifier	Accuracy	Precision	Recall	F-Measure
Support Vector Machine (SVM)	91.25	0.91	0.90	0.90
Naive Bayes (NB)	86.25	0.86	0.85	0.86
Multi-Layer Perceptron (MLP)	83.0	0.83	0.82	0.83
Logistic Regression (LR)	81.9	0.81	0.80	0.81
K-Nearest Neighbour (KNN)	81.9	0.81	0.80	0.81
Random Forest (RT)	86.0	0.86	0.85	0.86

C. Interface Tracking and Applications

The computational complexity and ML results are integrated into our database in order to create regional mobility profiles

TABLE II
MOBILITY PREDICTION CLASSIFICATION FOR DIFFERENT TRANSPORTATION REGIONS

Machine Learning Classifier	**Accuracy**	**Precision**	**Recall**	**F-Measure**
Support Vector Machine (SVM)	84.23	0.84	0.82	0.82
Naive Bayes (NB)	82.51	0.82	0.81	0.82
Multi-Layer Perceptron (MLP)	81.56	0.81	0.81	0.81
Logistic Regression (LR)	80.36	0.80	0.79	0.80
K-Nearest Neighbour (KNN)	79.57	0.79	0.78	0.79
Random Forest (RT)	84.5	0.84	0.83	0.84

as shown in Table III. This is being done for, (i) different transport modes such as driving, walking, and transit, and (ii) transportation in six regions, for which the classification results are shown in Tables I and II. Mobility database predicts the possibility of COVID-19 with the highest possible accuracy before and after the pandemic. Thus, creating perfect interface-tracing and alerting system classified by travellers in six worldwide regions. This will replace the manual intervention in the specific regions mentioned in Figs. 1 and 2. In this way, interface-tracking assistance can be given to the people who seek statistical reports for various applications such as; to develop location-based emergency procedures, alerting system, self-isolation, precautionary measures, geofencing dynamics of set boundaries to assess real world COVID scenario, etc. Our proposed framework with interface-tracking phenomenon

TABLE III
TRAVELLERS PROFILING DATASET

Age	Classification of the age group based on our dataset
Mode	Driving, transit, or walking
Regions	Europe, America, Africa, Asia, Australasia, or Middle-East
Vaccinated	Single or double jabbed
Symptoms	Fever, dizziness, breathing difficulty, or dry cough
Conditions	Asthma, heart ailments, chronic lung disorders, diabetes or gastro-intestinal Ailments.
Contact	Traveller close contact with other COVID-19 patient due recent regional travel, or engaged in public exposed zones.
Severity	The level of virus present Yes, or No. Which variant?

whose flow diagram is shown in Fig. 2. First the traveller profiles gets developed when travellers use one of the transportation modes followed by the regions they have traversed through. These movements get populated into an interface-tracking database which performs multiple functions when other travellers in close proximity to one another. Every location-based movements are recorded and tracked to maintain travellers profiling. Based on this information, alerts of hot-spots and proximity of pandemic affected travellers are being activated for avoidance of risky spots. The feature of geofencing introduces accuracy of movement of travellers into the system whether they are overground or in underground tunnels. The profiles of travellers continuously address the statuses whenever any movement occurs.

IV. CONCLUSION

Our novel mobility trends dataset focuses on the regional transportation modes under the COVID-19 pandemic. Worldwide transportation sector dynamics have been changed and possibly take a long time before full recovery. Therefore, we have introduced a new strategy to assess the transportation sector for any given smart city supported by mobility prediction accuracies using ML classifiers. Our results show the accuracy of 91.21% and 84.5% using SVM and RT algorithms for different transportation modes and regions. We also provide interface-tracking mechanism for sustainable and reliable transportation trends affected by the pandemic using travellers mobility profiling. For this, number of metrics are used to assess the mobility trends of the travellers in different regions using different modes to develop a database. Using the proposed technique, it is likely to have huge demand in the transportation sector when operational capacity approaches to maximum where necessary safety measures would be required. Also, reasonable modifications to the current transport systems with environmentally benign solutions would be needed as a lucrative opportunity. Finally, identification of revenue generation sources to remain profitable is essential without increasing fares or extra regional charges.

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