A Multi-Task Learning Framework for COVID-19 Monitoring and Prediction of PPE Demand in Community Health Centres

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Abstract—Currently, the world seeks to find appropriate mitigation techniques to control and prevent the spread of the new SARS-CoV-2. In our paper herein, we present a peculiar Multi-Task Learning framework that jointly predicts the effect of SARS-CoV-2 as well as Personal-Protective-Equipment consumption in Community Health Centres with respect to a given socially interacting populace. Predicting the effect of the virus (SARS-CoV-2), via studies and analyses, enables us to understand the nature of SARS-CoV-2, with reference to factors that promote its growth and spread. Therefore, these foster widespread awareness; and the populace can become more proactive and cautious so as to mitigate the spread of Corona Virus Disease 2019 (COVID-19). Furthermore, understanding and predicting the demand for Personal Protective Equipment promotes the efficiency and safety of healthcare workers in Community Health Centres. Owing to the novel nature and strains of SARS-CoV-2, relatively few literature and research exist in this regard. These existing literature have attempted to solve the problem statement(s) using either Agent-based Models, Machine Learning Models, or Mathematical Models. In view of this, our work herein adds to existing literature via modeling our problem statements as Multi-Task Learning problems. Results from our research indicate that government actions and human factors are the most significant determinants that influence the spread of SARS-CoV-2.

Index Terms—COVID-19, PPE, Multi-Task Learning, Multi-Task Optimization, Transfer Learning

I. INTRODUCTION

The Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) is a new form of enveloped Ribonucleic Acid (RNA) virus, responsible for the COVID-19 pandemic, and it has never been witnessed before December 2019. COVID-19 global epidemiological summaries report that there have been over 110,384,747 confirmed/positive cases as well as 2,446,008 deaths as a result of SARS-CoV-2. Moreover, these global epidemiological summaries are quite overwhelming. Therefore, the COVID-19 pandemic requires urgent and crucial input as well as measures from every domain. From a Data Science perspective, it is noteworthy that the world can be conceptualized as one big data problem.

With respect to the 21st century, data essentially influences and controls virtually everything that we tend to accomplish. For us, as a human race, to successfully conquer the COVID-19 pandemic; we require sufficient knowledge about the SARS-CoV-2. Thus, the quest for knowledge associated with the SARS-CoV-2 can only be acquired from information available about the virus. In turn, information is valuable resource which we can only extract from data. For that reason, there lies the importance of data and Data Science with respect to combating the COVID-19 pandemic.

Our work herein concentrates and proposes solutions to the following problem statements, namely:

i. Monitor the effect of SARS-CoV-2 via effective predictions of estimates with respect to Infected/Positive cases (Infected), Hospitalization cases (Hospitalized), Recovery cases (Recovered) and Death/Mortality cases (Death).

ii. Predict the demand of Personal Protective Equipment (PPE) by Community Health Centres (CHC) that provide medical treatment to COVID-19 (Hospitalized) patients.

With respect to our experiments and results, we have used the Canadian province of Ontario as our case study.

At the moment, there exist four (4) prevalent variants/strains of SARS-CoV-2 around the world. These strains are, namely: Lineage B.1.1.7 (UK/British variant), Lineage B.1.351 (South African variant), Lineage P.1 (Brazilian variant) and Lineage B.1.617 (Indian variant). Our research contributions and novelties herein cannot be downplayed considering the potential consequences of these emerging strains, and the current global impact of COVID-19. From one viewpoint, we have been able to identify several factors (Biological, Environmental, Government Actions, and Human), which influence the spread of SARS-CoV-2 by means of studies, experiments, and analyses. Also, we have been able to effectively forecast estimates of COVID-19 impact with respect to Infected, Hospitalized, Recovered, and Death cases. Consequently, these contributions can serve as control as well.
as preventive measures in curtailling the spread of SARS-CoV-2. Similarly, these contributions can be employed in clinical research and trials, with respect to drug and vaccine development, against SARS-CoV-2. From another viewpoint, we have proposed a model that forecasts PPE demand in CHC, with regard to the COVID-19 pandemic. Considering the safety of our frontline healthcare workers, this contribution serves as a preventive and control measure toward their protection. Also, this can serve as a proactive measure toward ensuring a robust supply network of PPE to CHC.

Furthermore, the (two) aforementioned problem statements have been modeled and analyzed as regression-based problems. Hence, we have employed a Multi-Task Learning (MTL) methodology with reference to the development and implementation of our proposed framework. Our parallel Transfer Learning (TL) model tackles the problem statements herein via pre-training on datasets, which are comprised of $i \times 13$ feature vector (row vector), collected from six (6) distinct Canadian provinces, viz: Alberta, British Columbia, Manitoba, New Brunswick, Quebec, and Saskatchewan. Subsequently, the resultant pre-trained model is referenced, as a source point for the transfer of learning and knowledge, for training another (dedicated) model concerned with the resolution of problems relating to our case study (Ontario province).

Our research introduces the following novelties, viz:

1. The parallel transfer of learning from correlated (source) domains to a target domain, via pre-training a MTL framework, yields much better generalization results with respect to COVID-19 monitoring.
2. Identification of influential factors, based on four (4) categories (SARS-CoV-2 Biological Factors, Environmental Factors, Government Actions, and Human Factors), which affect the spread of COVID-19.
3. Human factors (precisely age-group stratification) most significantly influence the rates of Infected cases, Hospitalized cases, and Death cases.
4. Government Actions (precisely vaccination, pandemic wave) most significantly influence Recovered cases rate.
5. We identified that COVID-19 is most prevalent among males and females, within the age group of 0 to 34, in a given socially interacting populace (see Figure 4).
6. Proposition of a model for the prediction of PPE demand (by CHC) with regard to COVID-19 Hospitalized cases.
7. Detailed evaluation and performance reports based on classic Machine Learning (ML) objective functions.

Our work presented hereafter is organized as follows: section II reviews a selected list of related literature. Section III formally defines the problem statement as well as the details of our proposed framework. Section IV expatiates on the datasets and materials used to facilitate our experiments. Section V documents the detailed results of our benchmark experiments; also, it captures our analyses, discussions, and conclusion.

II. HISTORICAL FOUNDATION AND RELATED LITERATURE

Several literature and published work, which aimed at resolving problems related to epidemiology, can be classified into three (3) broad categories, namely: Conceptual Models, Compartmental Models, and Computational Models.

A. Conceptual Models

Models in this category are essentially high-level representations, based on abstract ideas and notions, which illustrate how these models operate with regard to resolving targeted problems in epidemiology. A common shortcoming of these models is that they are simplistic, abstract, and usually not empirical.\(^2\),\(^3\),\(^4\), and\(^5\) primarily employed conceptual modeling toward resolving research problems in epidemiology.

B. Compartmental Models

Basically, these models are Mathematical Models which are based on a series of mathematical equations. They are employed in studying and analyzing how infectious diseases spread and affect different compartments of a given socially interacting populace. Also, they have been used to forecast the potential outcomes of endemics, epidemics, and pandemics. One drawback of these models is that some of them tend to be relatively complex. Common models in this category include, namely: Susceptible-Infected-Recovered (SIR) model \(^6\), Susceptible-Infected-Recovered-Deceased (SIRD) model \(^6\), Susceptible-Infected-Susceptible (SIS) model \(^6\), MaternallyDerivedImmunity-Susceptible-Infected-Recovered (MSIR) model \(^7\), Susceptible-Exposed-Infectious-Recovered (SEIR) model \(^7\), Susceptible-Exposed-Infectious-Susceptible (SEIS) model \(^7\), Susceptible-UnquarantinedInfectected-QuarantinedInfectected-ConfirmedInfected (SUQC) model \(^8\), etc.

C. Computational Models

In this category, there exist two (2) major subcategories of models used for epidemiology-related problems, viz: Agent-based Models and Machine Learning models.

On one hand, an Agent-based Model (ABM) is a computational model that re-creates a system, via simultaneously simulating the interactions of several autonomous agents, with the goal of analyzing and predicting potential event(s) about the given system. A popular downside of these models is that they tend to oversimplify, thereby yielding unauthentic predictions. Research which employed ABM for COVID-19 related problems include, viz: \(^9\), \(^10\), \(^11\), \(^12\), etc.

On the other hand, a ML model is an Artificial Intelligence (AI) approach such that a computational model is constructed, via learning from sample (or training) data, so as to extract inherent patterns about a given system which will be applied in making predictions/decisions about the given system. A common challenge with employing these models is the availability of good and sufficient sample data for training these models. Literature which have employed ML approach toward resolving COVID-19-related problems include: \(^13\), \(^14\), etc.

III. PROPOSED FRAMEWORK AND METHODOLOGY

This section is subdivided into three (3) subsections, namely: subsection III-A (problem definition), subsection III-B
(proposed methodology), and subsection III-C (proposed system framework and algorithms).

A. Definition of Problem

**Definition III.1.** **[COVID-19 Monitoring]**: Given a set of feature (independent) variables, \( X \in \mathbb{R} : x_{i,1}, x_{i,2}, ..., x_{i,j}, \) such that the shape of the feature space is an \( i \times j \) feature vector; and a set of target (dependent) variables, \( Y \in \mathbb{Z} : y_{1,1}, y_{1,2}, ..., y_{1,k}, \) such that the shape of the target space is an \( i \times k \) target vector. Our [COVID-19 Monitoring framework] aims at training a ML function, \( f_m : X \rightarrow Y \equiv x_{i,*} \mapsto y_{i,*} \), which learns to effectively make predictions about \( Y \) based on the patterns of information learnt from \( X \). Thus, \( y_{i,*} \in Y = f_m(x_{i,*} \in X) \).

B. Proposed Methodology

1) Feature Engineering Layer: Taking into consideration a socially interacting populace; the feature space of our MTL framework is established with respect to four (4) categories of influential factors, namely: SARS-CoV-2 Biological Factors, Environmental Factors, Government Actions, and Human Factors. These factors tend to affect the spread of COVID-19 with reference to a given populace. Features have been aggregated, based on the aforementioned categories of influential factors, with reference to any given population. Therefore, the initial or primary feature space is an \( i \times 27 \) feature vector with an elastic sample span. Table I provides detailed description(s) of each constituent feature for the \( i \times 27 \) feature vector.

2) Feature Extraction Layer: Furthermore, based on a basic examination of the initial/primary feature space, we were able to extract derived/secondary features. These derived features were computed via the application of arithmetic ratios and proportions to selected features of the initial/primary feature space. Therefore, the shape of the derived/secondary feature space is an \( i \times 44 \) feature vector with an elastic sample span. Also, the linear concatenation of the initial (primary) feature space, \( i \times 27 \), and the derived (secondary) feature spaces, \( i \times 17 \), temporarily expands our overall feature space to an \( i \times 44 \) feature vector.

3) Feature Selection Layer: In this layer, the dimensionality of the overall feature space, \( i \times 44 \) feature vector, is effectively and efficiently reduced to yield a feature space comprising only highly relevant features. These relevant features possess a high-degree influence with respect to the prediction of the target (or dependent) variables. Considering our study herein and experiment framework, on one hand, the shape of the final feature space of our model is an \( i \times 13 \) feature vector. This means that our proposed model learns to generalize based only on 13 highly relevant features per dataset.

On the other hand, the target variables comprise, viz:

1. **SARS-CoV-2 infection predictions** \( \text{Infected} \ (y_{*,1} \subseteq Y^I) \).
2. Predictions of hospitalized COVID-19 patients \( \text{Hospitalized} \) \( y_{*,2} \subseteq Y^H \).
3. Predictions of patients’ recoveries from COVID-19 \( \text{Recovered} \) \( y_{*,3} \subseteq Y^R \).
4. COVID-19 related death predictions \( \text{Death} \) \( y_{*,4} \subseteq Y^D \).

**Table I**: Primary features constituting the feature space of our framework [15]–[17].

| Category                  | Code   | Feature Name              | Description or Details of Feature                          |
|---------------------------|--------|---------------------------|-----------------------------------------------------------|
| Biological Factors        | feat   | Virus Reprod. Index       | The Effective Reproduction Number of SARS-CoV2            |
| Environment Factors       | feat   | Climate                   | Canadian seasonal periods of the year (1 = Spring, 2 = Summer, 3 = Autumn, 4 = Winter). |
|                           | feat   | Dry Land                  | Area (in km²) of land inhabited by the populace; exclusive of aquatic habitat. |
|                           | feat   | Region                    | Numeric encoding of each region/province (0 = Alberta, 1 = British Columbia, 2 = Manitoba, 3 = New Brunswick, 4 = Newfoundland and Labrador, 5 = Nova Scotia, 6 = Ontario, 7 = Prince Edward Island, 8 = Quebec, 9 = Saskatchewan). |
| Government Actions        | feat   | Wave                      | Pandemic phase (1 = first wave, 2 = second wave). |
|                           | feat   | Cumm. Vacc.                | Cumulative record of inoculated persons.                |
|                           | feat   | Lockdown                   | Stages of restrictions with regard to public health safety (1 = Lockdown scenario, 2 = Partial/Restricted reopening, 3 = Total/Full reopening). |
|                           | feat   | Travel Restrict           | Implementation of travel restrictions (0 = No restriction, 1 = Local government restriction, 2 = Provincial government restriction). |
|                           | feat   | Province FaceCover        | Implementation of compulsory face covering (0 = Not compulsory, 1 = Mandatory/Compulsory). |
|                           | feat   | Holiday                   | Effective days of holiday (0 = Workday, 1 = Holiday). |
| Human Factors             | feat   | Return Travellers          | Number of travelers returning to this region as their destination. |
|                           | feat   | Employ Rate               | Employment rate (%) of the region or province. |
|                           | feat   | Labor Popln               | Eligible workforce for the region or province. |
|                           | feat   | 0 - 34 (M)                | Male populace of age range: 0 - 34. |
|                           | feat   | 35 - 69 (M)               | Male populace of age range: 35 - 69. |
|                           | feat   | 70 - Above (M)            | Male populace of age range: 70 and above. |
|                           | feat   | 0 - 34 (F)                | Female populace of age range: 0 - 34. |
|                           | feat   | 35 - 69 (F)               | Female populace of age range: 35 - 69. |
|                           | feat   | 70 - Above (F)            | Female populace of age range: 70 and above.       |

Table I and Figure I provide in detail the 13 highly relevant features which constitute the final feature space. The relevance score with respect to each target or dependent variable is indicated via columns: **Infected**, ‘Hospital’, ‘Recover’, and **Death**, respectively.
TABLE II: Highly relevant features constituting the final feature space of our [MTL] framework.

| Category | Code | Final (or Highly Relevant) Features | Relevance Score per Target Variable |
|-----------|------|------------------------------------|------------------------------------|
| Infected  | feat_05 | Wave                               | 100%                               |
| Hospital  | feat_23 | 35 - 69 (M)                        | 85%                                |
| Recover   | feat_21 | Labor Popln                        | 83%                                |
| Death     | feat_24 | 70 - Above (M)                     | 83%                                |
| Relevant  | feat_27 | 70 - Above (F)                     | 82%                                |
| Features  | feat_26 | 35 - 69 (F)                        | 82%                                |
| or Factors| feat_22 | 0 - 34 (M)                         | 81%                                |
|          | feat_25 | 0 - 34 (F)                         | 81%                                |
|          | feat_11 | CHCentres                          | 76%                                |
|          | feat_00 | Cumm. Vac. change                  | 68%                                |
|          | feat_03 | Dry Land                           | 64%                                |
|          | feat_17 | residential change                 | 51%                                |
|          | feat_07 | Lockdown                           | 23%                                |

Fig. 1: Fishbone diagram of the relevant features affecting COVID-19 cases (case study = Ontario, Canada).

4) Feature Scaling Layer: After reviewing the final feature/independent variables of our data distribution, we noticed a lot of skewness in the data representation of the features. This problem of skewness, within the feature space, has to be overcome so as to improve the effectiveness of our model.

The constituent data of every feature variable, in the feature space, has been standardized (column-wise) to a standard normal data-distribution by means of Nonlinear Data Transformation [18] techniques as expressed in equation 1.

\[
F(x_{i,j}) \equiv \mathbb{P}(x_{i,j} \leq X) = p_{x,j} \in [0, 1], \quad X \in \mathbb{R}
\]

\[
q_{x,j} \in Q \equiv F^{-1}(p_{x,j}) = \min\{x_{i,j} \in \mathbb{R} : F(x_{i,j}) \geq p_{x,j}\}
\]

\[
z_{i,*} \in Z = \frac{q_{x,j} - \mu}{\sigma} \quad \text{Standard Score (Z) function}
\]

In equation 1, \(F\) and \(F^{-1}\) denote the Cumulative Distribution and Quantile functions, respectively. Consequently, the output \(q\) of the Quantile function is centered, on a mean \(\mu = 0.0\) and a standard deviation \(\sigma = 1.0\), to yield a standard normal distribution \(Z\). Thereafter, each standard-normal row/sample, \(z_{i,*} \in Z\), of the feature space has been normalized (row-wise) to yield a unit vector via L2-Normalization [19] technique as denoted in equation 2. \(i\) and \(j\) denote the dimensions of the rows and columns per feature vector.

\[
\tilde{z}_{i,*} \in \mathbb{R} \equiv \sum_{a=1}^{j} (z_{i,a})^2 = (z_{i,1})^2 + (z_{i,2})^2 + \ldots + (z_{i,j})^2 = 1
\]

Taking the dependent variables into consideration, the constituents of the target space have been transformed (column-wise) to a real distribution, \(0 \leq \tilde{z}_{i,*} \leq 1\), by means of MinMaxScaler [18] technique as expressed in equation 3.

\[
y'_{*,k} \in Y' \equiv G(Y) = \frac{y_{*,k} - \min(y_{*,k})}{\max(y_{*,k}) - \min(y_{*,k})}, \quad Y \in \mathbb{Z}
\]

\(i\) and \(k\) denote the dimensions of the rows and columns per target vector.

C. Proposed System Architecture and Algorithms

Training a Machine Learning model solely on COVID-19 daily records, which are based on one regional or provincial dataset, has a great tendency for overfitting on the training dataset and/or underfitting on the validation and test datasets. At the moment, COVID-19 daily records spans approximately 450 records (that is 1 record per day). Thus, a training dataset comprising barely 450 records tend to yield a relatively low degree of freedom, with respect to the feature space or independent variables, during ML training. In a bid to overcome these aforementioned challenges, we have adopted a Multi-Task Learning technique, as represented via Figure 2 and Algorithm 1 to effectively improve the generalization results with respect to COVID-19 monitoring.

On one hand, we have trained a Generic ML-model component on datasets aggregated from several provinces in Canada (exclusive of the province referenced as the case study). On the other hand, we have pre-trained a Dedicated ML-model component via Transfer of Learning from the Generic ML-model component. Subsequently, the Dedicated ML-model component is further trained using datasets acquired from the case study province or region.

Generalizations, with regard to predictions for the case study province, are effectuated via the Dedicated ML-model component of our MTL framework. Thus, the high point of our proposed MTL framework is that it can be readily adapted for making generalizations about any province/region. This is achieved by simply interchanging the regional dataset used for training the Dedicated ML-model component with a regional dataset used for training the Generic ML-model component.
Algorithm 1: Multi-Task Learning for COVID-19 Monitoring
/* See Table I */
Input: \{X : x_{s,1}, x_{s,2}, ..., x_{s,13}\} \subseteq \{X_{Generic}, X_{*\,\,s}\} /* See subsection III-B3 */
Output: \{Y : y_{s,1}, y_{s,2}, y_{s,3} : y_{s,4}\} \subseteq \{Y_{Generic}, Y_{\,\,s\,\,Dedicated}\}
Data: Regional datasets for \(k = 1\) to \(4\)

1 Program Main(X, Y):
   /* Scaling: See subsection III-B4 */
   for \(j = 1\) to \(13\) do
     \[ F(x_{s,j} \in X) \equiv p_{j} \, q_{j} \quad \text{where} \quad x_{s,j} = \min{x_{s,j} \in \mathbb{R}} \leq X \]
     \[ z_{s,j} \in Z = \frac{q_{j} - \mu}{\sigma}, \quad \mu = 0.0, \quad \sigma = 1.0 \]
   for \(k = 1\) to \(4\) do
     \[ y_{s,k} \in Y' = \frac{y_{s,k} - \min(y_{s,k})}{\max(y_{s,k}) - \min(y_{s,k})}, \quad Y' \in \mathbb{Z} \]
   \[ f_{Generic} : Y'_s \rightarrow Y_{Generic} \]
   \[ f_{\,\,s\,\,Dedicated} = f_{\,\,s\,\,Dedicated} + f_{\,\,Generic} \]
   \[ Y_{\,\,s\,\,Dedicated} = f_{\,\,s\,\,Dedicated}(Z_{\,\,s\,\,Dedicated}) \]
   return \(Y_{\,\,s\,\,Dedicated}\)

Algorithm 2: PPE Consumption/Demand Prediction in CHCs
/* See Figure 3 */
Input: \(y_{s,2} \subseteq Y'_{\,\,s\,\,11}, \text{OprCap, Personnel}\)
/* See Figure 3 */
Output: | PPE Kits |
Function ppeDemandPred(Y',feat_11,OprCap, Personnel):
   /* Initialize: Variables/Parameters */
   \(y_{s,2} \subseteq Y'_{\,\,s\,\,11} \subseteq \mathbb{Z}\)
   /* Available COVID-19 workforce */
   \(\text{Personnel} = \text{MedLabs} + \text{ParaMeds} + \text{DoctAssts} + \text{Doct} + \text{Nurses} + \text{RespThpts}\)
   \(\text{PPE Kits}_{s,i} = 0\) // Predicted PPE kit(s)
   for \(i = 0\) to \(m\) do
     \[ HspRtio_i = \frac{y_{s,2}}{\text{feat}_11} \]
     if \(HspRtio_i > 1.0\) then
       \[ \text{PPE Kits}_{s,i} = \text{OprCap}_i \times \text{Personnel}_i \times 1.0 \]
     else
       \[ \text{PPE Kits}_{s,i} = \text{OprCap}_i \times \text{Personnel}_i \times HspRtio_i \]
     return \(\text{PPE Kits}_{s,i}\)

Fig. 2: Proposed MTL framework for COVID-19 monitoring.

Fig. 3: Proposed architecture to predict PPE demand in CHC.

Figure 3 and Algorithm 2 showcase our proposed model with regard to the prediction of PPE demand(s), by provincial CHCs, in relation to the COVID-19 pandemic. We have employed an interpolation technique herein, which relies on the
predictions of hospitalized COVID-19 patients \(y_{i,2} \subseteq Y^H\).

For each \(i^{th}\) day prediction of PPE demand by a CHC, we instantiate Algorithm 2 and initialize the following variables:
1) \(i^{th}\) day prediction, \(\text{Hospitalized COVID-19 cases} (y_{i,2})\);
2) \(i^{th}\) day count of operational (regional) CHCs \(\text{(feat}_{11_i}^\text{)}\);
3) \(i^{th}\) day average operating capacity of available COVID-19 related workforce within regional CHCs \(\text{(OprCap}_i\text{)}\);
4) The \(i^{th}\) day count of available frontline COVID-19 related workforce \(\text{(Personnel}_i\text{)}\) within regional CHCs.

Subsequently, we compute the \(i^{th}\) day value for the dependent variable, \(\text{HspRtio}_i\), which denotes the average number of \(\text{Hospitalized COVID-19}\) patients per CHC in each region. In other words, \(\text{HspRtio}_i = y_{i,2} : \text{feat}_{11_i}^\text{)}\).

Afterwards, if \(\text{HspRtio}_i \geq 1\) is true, we indicates that there exist at least 1 \(\text{Hospitalized COVID-19}\) patient in every CHC for each region/province. Hence, we estimate the \(\text{PPE Kits}_i\) for the \(i^{th}\) day as the product: \(\text{OprCap}_i \times \text{Personnel}_i \times 1.0\).

However, if \(\text{HspRtio}_i < 1\) is true, it indicates that there exist some CHCs in each region with null \(\text{Hospitalized COVID-19}\) patient. Therefore, we estimate the \(\text{PPE Kits}_i\) for that \(i^{th}\) day as the product: \(\text{OprCap}_i \times \text{Personnel}_i \times \text{HspRtio}_i\).

### IV. MATERIALS AND METHODS

Table III gives a detailed overview of the COVID-19 datasets (per Canadian province) employed herein for our experiments. We have implemented the following objective functions, with respect to benchmarking our proposed MTL framework, namely: 
- **Coefficient of Determination** \((R^2)\)
- **Explained Variance Score** (EVS)
- **Mean Absolute Error** (MAE)
- **Root Mean Squared Error** (RMSE)
- **Training Time** (TT)

Also, to facilitate the implementation and evaluation of our work; we have included these libraries, viz: Scikit-Learn [18] and Keras [20]. The core regressor function of our proposed MTL model is based on k-nearest neighbors [18]. The k-nearest-neighbors regressor has been implemented using its default hyperparameters, as in Scikit-Learn [18] library, with exception to the \(n\_neighbors\) and \(weights\) parameters which we have tuned as: \(K\text{NeighborsRegressor}(n\_neighbors=6, weights='distance')\). Details regarding the reproducibility of our framework is available via: https://github.com/bhevencious/COVID-19-Monitor/blob/main/README.md

| Dataset | Start | End | Description |
|---------|-------|-----|-------------|
| Alberta | January 25th, 2020 | Each dataset, with regard to a province in Canada, contains variables of the target space and variables of the feature space. Every regional or provincial dataset comprises 362 rows which represent daily epidemiological records spanning from January 25th, 2020 to January 20th, 2021. |
| British Columbia | | | |
| Manitoba | | | |
| New Brunswick | January 20th, 2021 | | |
| Ontario | | | |
| Quebec | | | |
| Saskatchewan | | | |

### V. EXPERIMENTS, RESULTS, AND DISCUSSIONS

In our experiments and results stated herein (Tables IV, V, VI, and VII), we have rotated the training dataset for the Dedicated ML model component of our MTL framework across seven (7) distinct Canadian provinces (Alberta, British Columbia, Manitoba, New Brunswick, Ontario, Quebec, and Saskatchewan). Thus, any region/province used for training the Dedicated ML model component of our MTL framework is excluded from the training datasets for the Generic ML-model component of our MTL framework. The objective functions \((R^2, \text{EVS})\) and \((\text{MAE}, \text{RMSE}, \text{TT})\) attain their best at the values of 1.0 and 0.0, respectively.

Considering our experiment results in Table IV, Table VI, and Table VII; the prediction interval of our proposed MTL framework is based on a 95% confidence interval. Thus, as the respective values for \(R^2\) approach unity (1), they signify that our proposed MTL framework fits adequately to the COVID-19 dataset(s); and otherwise, as \(R^2\) approaches zero (0). In a similar fashion, as the respective values for EVS tend to unity (1), they explain to us that our proposed MTL model effectively captures and utilizes the data-point variations in the COVID-19 dataset(s). EVS explains otherwise as its respective values tend to zero (0). Moreover, MAE and RMSE compare the predictions from our proposed MTL model and the ground truth. As the respective values for MAE and RMSE approach zero (0), they imply that our MTL model makes predictions with relatively lower residual error(s).

Algorithm 2, proposed herein effects the prediction for PPE kits via interpolation into the predictions for Hospitalized cases. In consideration of the feature selection process carried out herein in subsection III-B3, we have observed that human-related factors (precisely peer groups) most significantly influence the rates of infected cases, hospitalized cases, and death cases as can be seen from Table II. Also, government actions (such as inoculation, pandemic wave, etc.) most significantly influence the rate of recovered cases as shown in Table II.

Figure 4 represents a distribution plot of COVID-19 prevalence across three major age groups in the province of Ontario (Canada). On one hand, we can see that youths (males and females whom fall within the age group of 0 to 34) greatly influence the spread of SARS-CoV-2 within a given socially interacting populace. On the other hand, seniors (males and females whom are of age 70 and above) are less likely to influence the spread of SARS-CoV-2 within a given socially
interacting populace. However, these seniors (age 70 and above) remain the most susceptible to SARS-CoV-2 due to several age-related risk factors.

A known limitation of this work is that the datasets employed herein for our experiments and analyses were gathered from the date range of January 25th, 2020 to January 20th, 2021. Hence, we assumed that these datasets represent and reflect casualties or cases with reference to the earliest variant of SARS-CoV-2 (UK/British variant). Consecutively, our assumption herein with regard to each unit of PPE kit is that it comprises five (5) items, namely: a face shield, a N95 respirator or face mask, a pair of hand gloves, a pair of shoe covers, and an overall isolation gown.

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