Explainable Models for Epidemiological Forecasting

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Introduction

- **Complex Modeling Challenge:**
  - Increasing reliance on sophisticated deep learning and statistical models for epidemiological forecasting
  - Complexity and opaqueness of these models obscure the understanding of influential factors
- **COVID-19 Context:**
  - The COVID-19 pandemic has accentuated the need for accurate epidemic forecasting
- **Issue with Interpretability:**
  - Difficulty in deciphering the rationale behind model predictions
  - Lack of transparency hinders effective early detection and response planning

Importance

- **Impact on Decision-Making:**
  - Essential for **informed decision-making** by governments and health organizations
  - Critical for planning **preemptive actions** during key phases of a pandemic
- **Targeted Policy-Making and Interventions:**
  - Enables the extraction of **key features** for early signal detection
  - Supports the design of targeted and effective **public health policies** and interventions
- **Broader Implications:**
  - Understanding model predictions is crucial for managing **large-scale epidemics**
  - Enhances **public trust and transparency** in health-related data and forecasting models.

Solution / Problem Formulation

- **Multivariate Time-Series Forecasting:**
  - Apply **VAR** and **LSTM** models for **forecasting future COVID-19 case counts** in 4 countries: **Japan**, **USA**, **France**, and **Italy**
- **Global Explainability Analysis:**
  - Use correlation to identify and rank predictive features for the forecasts for the entire 3-year period of the pandemic **("global")** from Jan 2020 to December 2022.
- **Local/Phased Explainability Analysis:**
  - Analyze predictive features during short, country-specific pandemic phases **("local")** of notable importance, particularly the Omicron outbreak, using SHAP values.
- **Cross-Regional and Cross-Phase Analysis:**
  - Compare and understand feature contributions and their variations across different countries and across different pandemic phases in USA.

DATASET – Collection + Processing + Analysis

Data Collection, Pre-Processing and Cleaning

- **Source:** Our main dataset comes from "Our World in Data" (OWID), covering the COVID-19 pandemic from January 2020 to September 2023. It includes data on cases, testing, vaccination, policy responses, and demographics.
- **Features & Description:** The OWID dataset is comprehensive with 67 feature columns, including epidemiological data (confirmed cases, ICU admissions, reproduction rate), testing data (total tests, new tests, positivity rates), vaccination metrics (doses administered, individuals vaccinated), policy responses (school closures, travel restrictions), and demographic data (population, median age, GDP per capita).
- **Data preprocessing & cleaning:** Data from 2020-2022 was used, with missing values imputed with zeroes, with no significant skew in distribution post-imputation. A missing value analysis showed the top five features with the most missing values.

Initial Data Analysis and Hypothesis

- **Analysis of Country Case Distribution**: Focused on four countries (Japan, USA, France, Italy) with high case counts, low fractions of imputed data, and span diverse geographical regions.
- **Initial Hypothesis:** Suspected correlation between case counts and other features, with specific time periods showing high spikes in new case counts.
- **Figure 1:** Time-series plots showing the correlation of various factors with daily new case counts for the four countries.

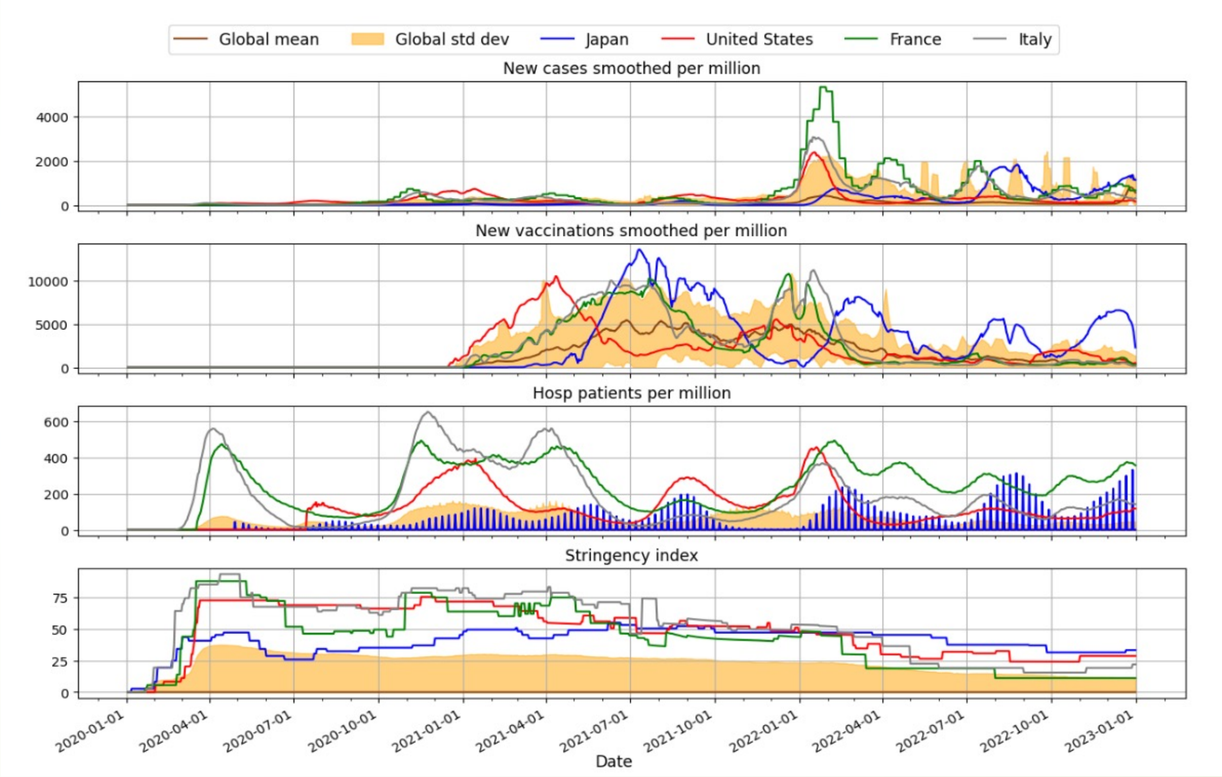

Figure 1: Comparative analysis of COVID-19 time-series data of daily new case count, daily new vaccination count, number of hospital patients, and government response stringency across the four chosen countries - "JPN", "USA", "FRA", "ITA"

Inferences from Initial Data Analysis

- **Correlation Insights:** Visual analysis suggests a correlation between rising case counts and other factors like vaccinations, hospital admissions and stringency index during certain periods.
- **Predictive Feature Set:** Hypothesize that these features might be crucial for forecasting case counts.
- **Notable Periods for Analysis:** Early 2022 (Omicron onset), late 2020 (pre-vaccine phase), and declining phase in 2022

METHODOLOGY

Forecasting Approaches

- **Roll-forward Validation**: To predict future COVID-19 case trends, we use a rolling-window or roll-forward validation method. This means we start with a fixed-size temporal subset of training set and validate predictions on next time step, dropping the least recent datapoint and adding the datapoint for the new time step as we move forward. This approach avoids "look-ahead" bias / peeking into the future
- **Target Variable**: For every country, we focus on forecasting "**new_cases_smoothed_per_million**", representing daily new confirmed COVID-19 cases *per million* people in the population, *smoothed* over 7 days
- **Key Features**: To enhance our multivariate forecast's accuracy, we include seven crucial time-series features that can potentially be predictive of case count forecast:
  - **ICU patients** *per million*
  - COVID-19 **reproduction rate**
  - **Hospital patients** *per million*
  - Daily **new people vaccinated** (*smoothed per hundred*)
  - **New vaccinations** (*smoothed per million*)
  - Government response **stringency index**
  - **Tests per confirmed** (positive) **case** (*smoothed*)

Forecasting Model Selection and Details

1. **Vector Autoregression (VAR)** :
   - A *statistical model* capturing linear relationships between multiple time series.
   - Involves ensuring stationarity (using Augmented Dickey-Fuller test), selecting the lag order, estimating the model, and forecasting future values.
2. **Long Short-Term Memory (LSTM)** :
   - Type of *recurrent neural network* (deep learning) adept at handling long sequences.
   - Process includes normalizing data, transforming into valid format **(use last 'n' time steps (days) to predict next time step)**, designing and training LSTM, and forecasting.

- **Performance Metrics:**
  - ***Mean Absolute Error (MAE)*** + ***Root Mean Square Error (RMSE)*** to evaluate model accuracy (and reliability for feature explainability analysis)
- **Bayesian Optimization:**
  - Used for hyperparameter (e.g. learning rate, architecture) tuning to optimize model
- **Data Splitting:**
  - Temporal split of the dataset over entire 3-year period into 80%-20% split of training / in-sample and testing / out-of-sample sets to assess performance.

Predictive Feature Explainability Analysis

	Global Analysis	Local / Phased Analysis	Cross-Phase Analysis*
Countries	All 4 (USA, ITA, JPN, FRA)	All 4 (USA, ITA, JPN, FRA)	USA only
Time Period	Entire 3-year period (Jan 2020 – Dec 2022)	One country-specific 21-day phase of ***fastest case count growth*** (Omicron outbreak onset (2022))	Three 21-day phases: 1. ***fastest growth pre-vaccines*** (2020) 2. ***fastest growth*** (Omicron onset) 3. ***fastest decline***
Metric	PCC – Pearson's Correlation Coefficient	SHAP (SHapley Additive exPlanations) values	SHAP (SHapley Additive exPlanations) values
Model (s)	VAR + LSTM	LSTM only	LSTM only

*Our Cross-Phase Analysis is a specialized extension of local analysis across multiple "local" phases of importance, but limited only to USA

Predictive Feature Explainability Analysis

- **Pearson Correlation Coefficient (PCC):**
  - Measures the linear relationship between feature value and case forecast
  - Ranges from -1 to 1, indicating the strength and direction (positive / negative) of the relationship.
  - Helps identify features that strongly correlate with COVID-19 case counts.
- **SHAP (SHapley Additive exPlanations) Values:**
  - Provide a unified measure of feature importance in machine learning models.
  - Decompose a model's prediction into contributions from each feature.
  - Allow for visualizing the impact of feature values on predictions, with positive SHAP values contributing to an increase and negative SHAP values contributing to a decrease in the forecasted case counts

RESULTS & DISCUSSION

Multivariate Time-Series Forecasting

- Models Used: Employed Vector Autoregression (VAR) and Long Short-Term Memory (LSTM) networks for forecasting new_cases_smoothed_per_million.
- Data Preparation and Model Configuration:
  - Data Split: 80%-20% train-test split, maintaining temporal order to avoid look-ahead bias.
  - Scaling: MinMax scaling for data normalization, crucial for effective modeling in both VAR and LSTM.
- VAR Model Insights: Lag Order Selection: Determined using Akaike Information Criterion (AIC) to balance model complexity and fit.
- LSTM Model Insights:
  - Historical Window: 20-day window to capture short-term temporal dependencies.
  - Model Architecture: LSTM layer with 128 nodes, two fully connected layers (64 and 32 nodes), and a final output layer.
  - Training Parameters: Trained for 100 epochs, batch size of 8, using MAE as the loss function, and Adam optimizer.

Forecasting Model Performance

- Evaluation Metrics: Performance evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).
- Results:
  - Table 1: Testing Error Metric Results (MAE and RMSE) for VAR and LSTM Models across Japan (JPN), USA, France (FRA), and Italy (ITA).
  - Highlight key findings: Both models showed robust and satisfactory performance, with specific metrics detailed in the table.

Model/Country	JPN	USA	FRA	ITA
Mean Absolute Error (MAE)				
VAR	448.487	72.264	172.839	88.437
LSTM	596.257	163.931	170.202	103.345
Root Mean Square Error (RMSE)				
VAR	633.451	95.006	208.542	114.720
LSTM	691.426	165.187	200.414	126.039

Table 1: Testing Error Metric Results - MAE and RMSE – for VAR and LSTM Models for all countries

Global Explainability Analysis – Results

Country	Model	Top Feature 1	Top Feature 2	Top Feature 3	Top Feature 4
JPN	VAR	new_vaccinations (0.245)	tests_per_case (-0.226)	hosp_patients (0.181)	icu_patients (0.108)
	LSTM	new_vaccinations (0.250)	tests_per_case (-0.246)	stringency_index (-0.225)	hosp_patients (0.205)
USA	VAR	hosp_patients (0.818)	icu_patients (0.664)	tests_per_case (-0.250)	stringency_index (-0.114)
	LSTM	hosp_patients (0.603)	icu_patients (0.506)	reproduction_rate (-0.282)	tests_per_case (-0.116)
FRA	VAR	hosp_patients (0.432)	tests_per_case (-0.316)	new_vaccinations (-0.214)	icu_patients (0.209)
	LSTM	hosp_patients (0.447)	tests_per_case (-0.307)	reproduction_rate (-0.274)	new_vaccinations (-0.164)
ITA	VAR	tests_per_case (-0.394)	hosp_patients (0.247)	new_vaccinations (-0.114)	stringency_index (-0.094)
	LSTM	tests_per_case (-0.386)	new_vaccinations (-0.285)	reproduction_rate (-0.267)	hosp_patients (0.179)

Top 4 most predictive features based on Pearson Correlation Coefficient (PCC) of features with LSTM and VAR forecasts for every country (sorted in decreasing order of absolute PCC - red = positive PCC, blue = negative PCC)

Global Explainability Analysis - Discussion (Country-Specific Insights)

- **Japan (JPN):** Counterintuitive positive correlation of **new vaccinations** with case counts, possibly due to the late surge of COVID-19 cases in JPN during the Omicron variant outbreak + aggressive vaccination campaigns (but not targeted against Omicron). Suggests the evolving efficacy of standard vaccines against new strains. Strong positive correlations for **hospital** and **ICU patients.**
- **United States (USA):** Strong positive correlations for **hospital** and **ICU patients**, reflecting the burden on healthcare systems.
- **France (FRA) and Italy (ITA):** Similar to the USA, **hospital patients** strongly correlate with case counts. Notably, **new_vaccinations** show a strong negative correlation, indicating the effective reduction in cases with increased vaccinations.

Global Explainability Analysis - Discussion (Cross-country Similarities + Differences)

- **Cross-Country Commonalities:**
  - **Hospital Patients and ICU Patients** :
    - Emerged as significant positively correlated predictors **in all countries**.
    - Validates our initial hypothesis based on time-series data analysis
  - **Stringency Index** :
    - Negative correlations in **ITA, USA, JPN** for certain models
    - Suggests increased government stringency potentially led to a reduction in cases
  - **Tests per case** (per confirmed positive case – inverse indicator):
    - Consistently showed a negative correlation **across all countries**
- **Cross-Country Differences:**
  - **New Vaccinations**:
    - Positive correlation in **JPN**, likely due to late surge and timing of Omicron variant.
    - Strong negative correlations in **FRA** and **ITA**, indicating possibly more effective vaccination campaigns in these countries

Local Explainability Analysis – Results

Country	Pred. Date	Predictive Features (Deduced from & sorted by absolute SHAP value for LSTM forecast)
JPN	July 29, 2022	1. hosp_patients (0.640), 2. icu_patients (0.446), 3. new_vaccinations (0.396), 4. reproduction_rate (0.321)
USA	Jan 3, 2022	1. icu_patients (0.679), 2. hosp_patients (0.665), 3. tests_per_case (0.063)
FRA	Jan 10, 2022	1. hosp_patients (0.657), 2. icu_patients (0.548), 3. tests_per_case (0.039)
ITA	Jan 10, 2022	1. new_vaccinations (-0.850), 2. hosp_patients (0.418), 3. icu_patients (0.369), 4. tests_per_case (0.022)

Predictive Local SHAP value Analysis for LSTM Model: 21-Day Peak COVID-19 Growth During Omicron Outbreak for every country (sorted in decreasing order of absolute SHAP value - red = positive SHAP, blue = negative SHAP)

Local Explainability Analysis - Discussion (Country-Specific Insights)

- **Japan (JPN):** A counterintuitive positive SHAP value for new vaccinations indicates that increased vaccinations coincided with a surge in cases, perhaps due to the late arrival of the Omicron wave or a delay in vaccine effectiveness against this variant. Suggests the evolving efficacy of standard vaccines against new strains. Strong positive SHAP values for **hospital** and **ICU patients.**
- **United States (USA) and France (FRA):** Strong positive SHAP values for **hospital** and **ICU patients**, reflecting the burden on healthcare systems.
- **Italy (ITA):** Similar to the USA and France, **hospital patients** and **ICU patients** also have high SHAP values. Notably, **new_vaccinations** show a strong negative SHAP value, indicating the effective reduction in cases with increased vaccinations.

Local Explainability Analysis - Discussion (Cross-country Similarities + Differences)

- **Cross-Country Commonalities:**
  - **Hospital Patients and ICU Patients** :
    - Revealed as consistently strong predictors with notably high POSITIVE SHAP values **across all countries**.
    - Validates our initial hypothesis based on time-series data analysis
- **Cross-Country Differences:**
  - **New Vaccinations**:
    - Strong positive SHAP value in **JPN**, likely due to late surge and timing of Omicron variant.
    - Strong negative SHAP value in **ITA**, indicating possibly more effective vaccination campaigns in these countries
  - **Reproduction Rate** (Quantifies how quickly the virus is spreading)
    - Showed a positive SHAP value in **JPN**, indicating its significant role during the surge, but it was not among the top predictors; was **not a good predictor in other countries**

Cross-Phase Explainability Analysis (USA only)- Results

Phase	Pred. Date	Predictive Features
Pre-Vaccine	Dec 2, 2020	1. icu_patients (0.792), 2. hosp_patients (0.626), 3. tests_per_case (0.150)
Fastest Increase (Omicron onset peak)	Jan 3, 2022	1. icu_patients (0.679), 2. hosp_patients (0.665), 3. tests_per_case (0.063)
Fastest Decline (After Omicron peak)	Mar 4, 2022	1. tests_per_case (-0.515), 2. icu_patients (-0.225), 3. hosp_patients (-0.207)

Table 4: Cross-Phase Analysis: Top predictive features based on SHAP values of contributions of features corresponding to LSTM model forecasts for different phases or periods of the pandemic for USA (sorted in decreasing order of absolute SHAP value - red = positive SHAP, blue = negative SHAP).

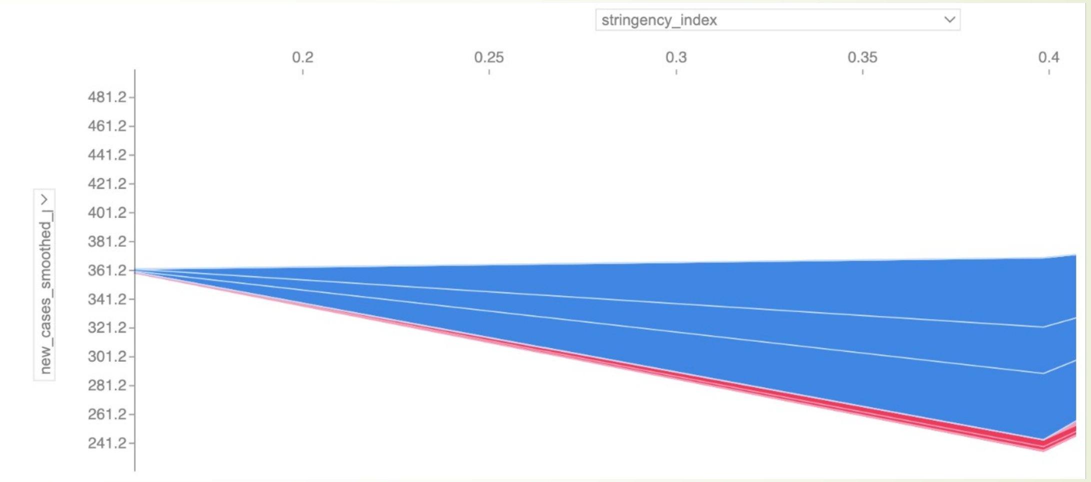

Figure 6: (APPENDIX) SHAP force plot illustrating the impact of the stringency index during the phase of fastest decline in COVID-19 cases (after first Omicron onset peak) in the USA. The plot shows the increase in stringency index correlating with the decrease in case counts.

Cross-Phase Explainability Analysis (USA only) - Discussion

- **Objective**: Investigating variance in predictive features across different pandemic phases in the USA using local SHAP value analysis of LSTM forecasts.
- **Phases Analyzed:**
  - <u>Pre-Vaccine Peak Phase (2020)</u>: Key features - ICU Patients, Hospital Patients, Tests per Case.
  - <u>Peak Phase During Omicron Outbreak (Q1 2022)</u>: Key features remained the same, indicating ongoing challenges in healthcare despite advancements.
  - <u>*Phase of Fastest Decline Post-Omicron Peak (2022)*</u>: Key features - Tests per Case, ICU Patients, Hospital Patients (all with high but negative SHAP values).
- **Special Observation for the Decline Phase**:
  - Notable change in stringency_index from 0.2 to 0.4 in the USA.
  - Increased stringency correlated with decreased case count forecast.
  - SHAP force plot for stringency_index (see Appendix Figure 6) demonstrates this impact.

Conclusion

- **Key Predictive Features:**
  - **Hospital patients** and **ICU patients** are crucial for predicting COVID-19 case trends, consistently evident across different analyses.
- **Significance of Vaccination Data:**
  - **New vaccinations** stand out as the second most predictive feature, underscoring the importance of vaccination efforts in pandemic dynamics, followed by **stringency index** and **reproduction rate**
- **Recommendations for Epidemic Management:**
  - Emphasize the need for integrating hospital / ICU patient and vaccination data into public health policies for better epidemic preparedness and response
- **Study's Broader Contribution:**
  - Reinforces the need for a comprehensive, data-driven approach in epidemic understanding and management.