Novel Multimodal Data for Enhanced Electricity Spot Price Forecasting Using A CNN-LSTM Ensemble Learning Model for the Japan Electric Power eXchange (JEPX) Spot Market

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***Abstract*—Electricity price forecasting (EPF) is critical in energy markets, particularly with the rise of renewable energy sources (RES) in Japan, which can cause day-ahead spot prices to drop to nearly zero JPY/kWh, impacting retailer profitability. This study demonstrates that the Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model outperforms the LSTM model in both prediction accuracy and computational efficiency in Japan's electricity spot market. A novel ensemble learning strategy enhances both the robustness and accuracy of the EPF model is proposed. Novel multimodal explanatory variables, including electricity spot price, system price, discretionary cost, sell bid amount, buy bid amount, total contracted volume, actual power generation, actual solar power generation, meteorological forecasts and calendar forecasts, alongside the rolling features of spot prices, are utilized and verified. Furthermore, a "policy-versus-policy" approach addresses the zero-inflated regression issue of the zero price prediction is proposed. Our model, with a comprehensive feature integration, achieves an RMSE of 5.66 JPY/kWh and an R^2 of 0.729 during the test range from 2022.01.01 to 2022.12.31. The paper also introduces a novel method for estimating confidence intervals using ensemble learning.**

***Index Terms*—electricity price forecasting (EPF), renewable energy source (RES), CNN-LSTM, ensemble learning, zero electricity spot price, confidence interval**

I. INTRODUCTION

In recent years, the increased penetration of RES, particularly from wind and solar sources, has introduced an unprecedented phenomenon in the US and EU electricity markets: negative electricity spot prices [1], [2]. However, the situation in Japan presents a distinct narrative. With the significant introduction of solar and wind energy into the Japanese power grid, the electricity wholesale spot markets have witnessed prices approaching nearly zero, specifically at 0.01 JPY/kWh (referred to as zero prices in the following sections of this paper). The electricity spot prices in Kyushu region, Japan, is depicted in Fig. 1(a). A closer look at the intermittent zero prices is presented in Fig. 1(b). As evident from Fig. 1(a), the emergence of considerable zero prices became prominent from the year 2020 onwards, largely attributable to the rapid integration of RES. In this evolving energy landscape, day-ahead electricity price forecasting (EPF) in electricity spot markets has emerged as a paramount concern [3]. Statistical models such as the Autoregressive Moving Average (ARMA) [4], [5] and Autoregressive Integrated Moving Average (ARIMA) [6]–[8] have been widely employed in EPF studies. While these models provide foundational approaches, their inherent linearity can pose challenges. The increased integration of RES, along with factors like demand fluctuations, introduces non-linear trends and sudden price anomalies that traditional statistical models may struggle to capture accurately.

Moreover, as is shown in Fig. 1(b), after data normalization, the considerable durations of zeros resulted by the zero prices in the target variable create a zero-inflated regression problem in machine learning. However, it is almost impossible for most machine learning models, including Random Forest (RF), Support Vector Regression (SVR), and neural networks, to continuously output zeros. Traditional solutions for zero-inflated regression problem usually requires two models: one classification model to identify zero values and another regression model for non-zero values, which doubles the training time and cost.

To address the challenges mentioned above, this paper's objective is to utilize multimodal data as novel features to enhance electricity spot price forecasting (EPF) in Kyushu region, Japan, using LSTM and CNN-LSTM prediction models. In addition, a novel ensemble learning approach is leveraged to further enhance the prediction accuracy of LSTM and CNN-LSTM due to the their inherent uncertainties. The performance of the LSTM and CNN-LSTM in EPF is compared in terms of both prediction accuracy and computation time. Moreover, to shoot the zero-inflated problem in the JEPX spot market, a novel "policy versus policy" strategy is employed to forecast the zero prices to half the computation time which traditional two-stage method requires. Furthermore, a natural logarithm transformation is utilized to improve the spot price's Skewness and Kurtosis to enhance prediction accuracy. Moreover, a novel method for extracting meteorological forecast data by utilizing Google Maps is introduced. Finally, an implication

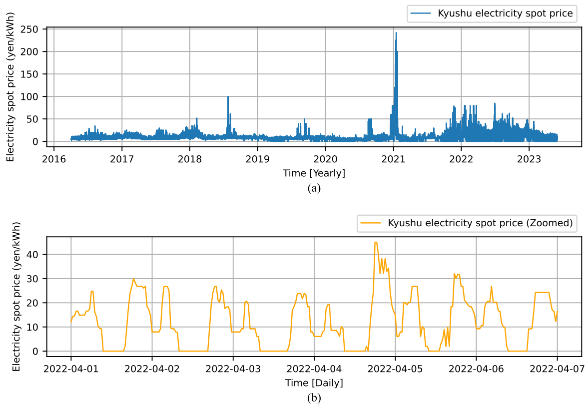

Figure 1. Kyushu electricity spot price [JPY/kWh] (a) and zooming-in zero-inflated prices (b).

of a novel estimation method for the confidence interval of EPF is demonstrated.

II. Methodology

A. LSTM and CNN-LSTM forecasting models

A LSTM model and CNN-LSTM model were designed and employed for EPF and for comparison using the Python Tensorflow keras library. The architectures of the LSTM and CNN-LSTM models are delineated in Fig. 2, the hyperparameters were selected empirically based on optimal performance.

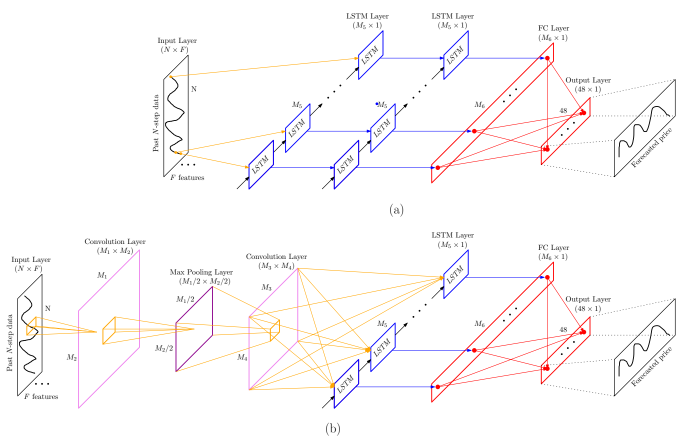

Figure 2. Schematic of the architectures of the (a) LSTM and (b) CNN-LSTM models.

B. Ensemble learning strategy

Given the inherent variability of neural network models due to their sensitivity to initial conditions and the stochastic nature of their training, training the same neural network multiple times and averaging the predictions can mitigate individual model errors, leading to enhanced prediction performance, as different models will not make identical errors on the test set [9], [10]. Based on this understanding, an ensemble learning approach was implemented. The CNN-LSTM and LSTM models underwent multiple training iterations. Subsequently, all individual predictions were aggregated using a simple averaging method to construct the final ensemble prediction, as depicted in (1), where N represents the total number of predictions, and k denotes the index of each individual prediction.

$$\hat{y}_{\text{ensemble}} = \frac{1}{N}\sum_{k=1}^{N}\hat{y}_k \tag{1}$$

For clarity, the pseudo-code for the ensemble learning procedure is outlined in **Algorithm 1**.

Algorithm 1 Ensemble Learning Procedure

1: Perform log transformation of the electricity spot price using (9).
2: Normalize the training and test data.
3: **for** $i = 1$ to 30 **do**
4: Train the model to generate prediction $\hat{y}_i$.
5: **end for**
6: Restore the predicted values to their original scale (reverse data normalization).
7: Apply the exponential transformation to the predicted values using (10) (reverse of the log transformation).
8: Calculate the ensemble prediction $\hat{y}_{\text{ensemble}}$ using (1).
9: Calculate the zero price for $\hat{y}_i$ and $\hat{y}_{\text{ensemble}}$ using (2).

C. "Policy-versus-policy" zero prices forecasting strategy

In this study, we introduce a novel method to address the zero-inflated regression problem of the EPF in JEPX spot market. The solution begins with understanding the broader trends in global electricity spot markets. As highlighted by Seel et al. [1], an abundance of RES can lead to negative electricity spot prices in the US and EU. Drawing from this, we infer that negative pricing is a natural consequence of RES abundance. In Japan, policy dictates that electricity spot prices cannot drop below 0.01 JPY/kWh, thereby preventing them from turning negative. Assuming that the circumstances leading to negative prices in the US and EU are similar to those in Japan, it is reasonable to infer that the explanatory variables in both scenarios would exhibit similar patterns. Feeding these Japanese explanatory variables into a machine learning regression model would naturally produce negative prices, as the model is not constrained by Japan's minimum pricing policy. Hence, by leveraging this premise, zero prices can be forecast by translating any negative outputs from the model to zeros, as indicated in **Algorithm 1**. This approach effectively functions as a policy-versus-policy forecasting strategy, reflecting real-world conditions. Equation (2) illustrates the zero price calculation procedure.

$$\hat{y}_i = \max(0, \hat{y}_i) \tag{2}$$

D. Performance evaluation

Performance metrics, including root mean squared error (RMSE) and the coefficient of determination (R^2), were utilized for evaluation. The computational formulae for RMSE and R^2 are specified in (3)-(4), respectively.

$$\mathrm{RMSE}(y, \hat{y}) = \sqrt{\frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{n}} \tag{3}$$

$$\mathrm{R}^2(y, \hat{y}) = 1 - \frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{\sum_{t=1}^{n} (y_t - \bar{y})^2} \tag{4}$$

III. Data Preparation

This study utilizes multimodal data for enhanced EPF, including the actual total power generation, actual solar power generation, spot price rolling features (minimum, maximum, mean, and standard deviation), system spot price, discretionary cost, sell bid amount, buy bid amount, total contracted volume, meteorological forecast data, and calendar forecast data. The overall data architecture and the corresponding time frame are illustrated in Fig. 3. The input data are segmented by their temporal deley into three green blocks. To maintain consistency with the Japan Electric Power Exchange (JEPX) spot price data, all input data were linearly interpolated to a time resolution of 30 min. A 7-day moving window was applied to the input data before being fed into the CNN-LSTM and LSTM models. In the JEPX spot market, all transactions must be finalized by the bidding deadline of 10:00 JST. To ensure an accurate and comprehensive prediction process, ample time is allocated for the execution and potential refinements of neural network calculations. Given the computational requirements and the complexities of the forecasting process, a 5-h buffer before the deadline has been established. The forecasting time point is set to 05:00 JST, covering the entire following day from 00:00 JST to 23:30 JST, which includes 48 time frames in total.

In this study, since photovoltaic (PV) power is the primary RES in the Kyushu region due to its substantially greater installed capacity compared to wind power, features pertaining to wind power are not incorporated into the current investigation.

A. Feature engineering

Feature engineering was conducted using a method that involves calculating rolling statistics (minimum, maximum, mean, and standard deviation) of the electricity spot price with a rolling window. This method is crucial for capturing temporal patterns and trends, which are essential for time series feature extraction. The length of the rolling window was chosen to be 24 h, i.e., w = 48. The equations for these calculations are provided in (5)-(8).

$$\mathrm{Min}_t = \min(y_{t-w+1}, y_{t-w+2}, ..., y_t) \tag{5}$$

$$\mathrm{Max}_t = \max(y_{t-w+1}, y_{t-w+2}, ..., y_t) \tag{6}$$

$$\mathrm{Mean}_t = \frac{1}{w} \sum_{i=t-w+1}^{t} y_i \tag{7}$$

$$\mathrm{Std}_t = \sqrt{\frac{1}{w-1} \sum_{i=t-w+1}^{t} (y_i - \mathrm{Mean}_t)^2} \tag{8}$$

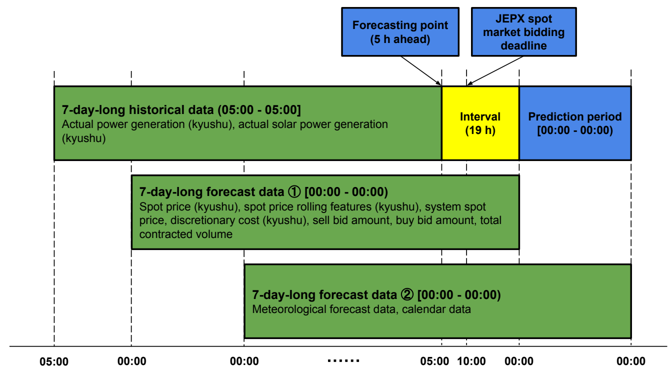

Figure 3. Illustration of the data architecture with a 30-min time interval, highlighting the time delays among different data.

B. Electricity data

The electricity spot prices (JPY/kWh) at a 30-min resolution, including the Kyushu regional spot price, system spot price, discretionary cost, sell bid amount, buy bid amount, and total contracted volume, from 00:00 JST to 23:30 JST (over a 7-day period), were downloaded from the Japan Electric Power Exchange (JEPX) [11].

The distribution of the Kyushu region electricity spot prices, as illustrated in Fig. 4(a), exhibits pronounced Skewness and Kurtosis, indicating a non-normal distribution. Neural network models typically assume that input data are normally distributed or, at least, exhibit symmetry in their distribution since this facilitates the model's learning process by providing a standardized scale of input features. Deviations from normality, such as Skewness and Kurtosis, can introduce biases in the model's predictions and affect the efficiency of the learning algorithm. To mitigate these effects, a natural logarithm transformation was applied to the electricity spot prices, as detailed in Fig. 9. This transformation is a common technique in statistical normalization that reduces the impact of Skewness by compressing the scale of the distribution, thereby enhancing symmetry and reducing the influence of outliers. The effectiveness of the logarithmic transformation is quantitatively evidenced by the reduction in Skewness and Kurtosis of the price data, as outlined in Table I. Following the model's prediction output, an exponential back-transformation, defined in (10), is applied to convert the forecasted values back to their original scale.

$$y = \log_e(y + 1) \tag{9}$$

$$y = e^{y} - 1 \tag{10}$$

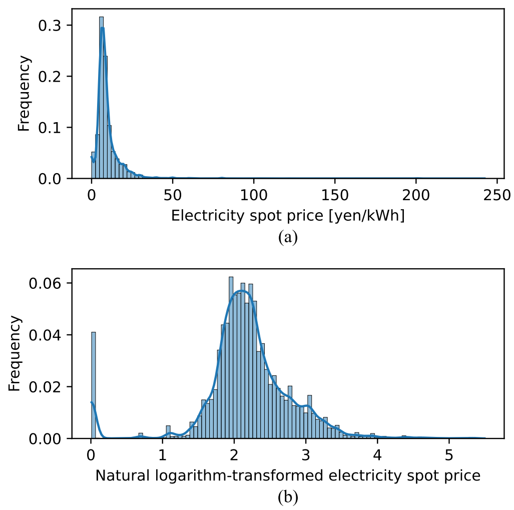

Figure 4. Distribution of Kyushu region's electricity spot prices (a) and the corresponding distribution after a natural logarithm transformation (b).

TABLE I. Skewness and Kurtosis of the original electricity spot price and the natural logarithm-transformed electricity spot price.

	Original	Log-transformed
Skewness	8.77	-0.68
Kurtosis	123.00	3.81

The actual electricity generation data (MW) at a 30-min resolution in the Kyushu region, including the actual power generation and actual solar power generation over a 7-day period from 05:00 JST to 05:30 JST, were downloaded from the Organization for Cross-regional Coordination of Transmission Operators, Japan (OCCTO) [12]. These data were used as input features and are depicted in the leftmost green block in Fig. 3.

C. Meteorological forecast data

The meteorological forecast data of Kyushu region, including the wind speed, air temperature, relative humidity, cloudiness, precipitation, solar radiation, were downloaded from the Japan Meteorological Business Support Center (JMBSC) [13], as illustrated in the rightmost green block in Fig. 3. The Kyushu region map was a rectangular screenshot from Google Maps Styling Wizard [14]. The identification of the land area from the Kyushu region map was conducted using the Python OpenCV library [15] applied to the screenshot image of Kyushu region from Google Maps. Fig. 5(a) displays the original screenshot of the map for the Kyushu region. In this step, pixels that are not within the defined blue color range are identified as land. Subsequently, Fig. 5(b) showcases the delineated land areas from Fig. 5(a), with red dots marking these regions. After the identification of land, the meteorological data of all the land area were averaged as input features.

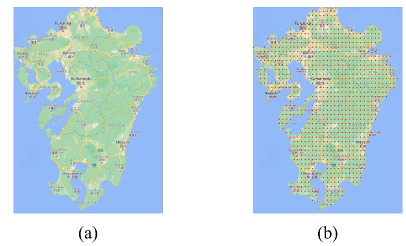

Figure 5. Kyushu area map (a) and the identified land areas (b). Map data: ©2024 Google, TMap Mobility.

D. Calendar forecast data

The calendar forecast data, by integrating the cyclic data and culturally significant Japanese holidays, aimed to enhance the EPF accuracy by accounting for the unique electricity consumption behaviors associated with these special occasions, covering a 7-day period from 00:00 JST to 23:30 JST, were used as features, as illustrated in the rightmost green block in Fig. 3.

1) Cyclic data: In this study, we employ sine and cosine transformations with periods corresponding to common cyclical patterns: 1 day, 1 week, 3 months, and 1 year. Such transformations have been acknowledged in foundational time series literature as a robust method to encapsulate periodic patterns in data [16]–[18]. The input features consist of the sine and cosine waves representing 1 day, 1 week, 3 months (seasonal effects), and 1 year. The sine and cosine waves with a period of 1 year is shown in Fig. 6.

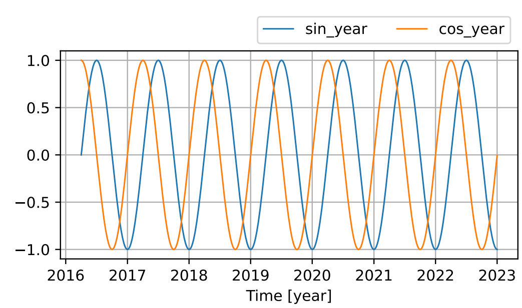

Figure 6. Sine and cosine waves with a period of 1 year.

2) Holiday data: The holidays and non-holidays were encoded into numerical labels 1 and 0, respectively.

E. Prediction approach

A One-time prediction schematic, shown in Fig. 7(b), is used to validate the proposed features as it requires much less training time compared with the day-by-day prediction schematic shown in Fig. 7(a). In this scenario, the training data spaned from April 1, 2016 — the date marking the full liberalization of the electricity retail market — to December 31, 2021. The testing data encompass the period from January 1, 2022 to December 31, 2022. All the features proposed in Section III has been validated for prediction accuracy enhancement.

After validating the proposed features using the test data which spans the entire 2022 year, the day-by-day prediction approach was conducted using all proposed features to explore the actual prediction accuracy in real-application scenarios, as illustrated in Fig. 7(a), which shares the same test range in the one-time prediction schematic. The training of the models was conducted using two NVIDIA Quadro RTX 8000 GPUs using the Python keras package in Windows OS.

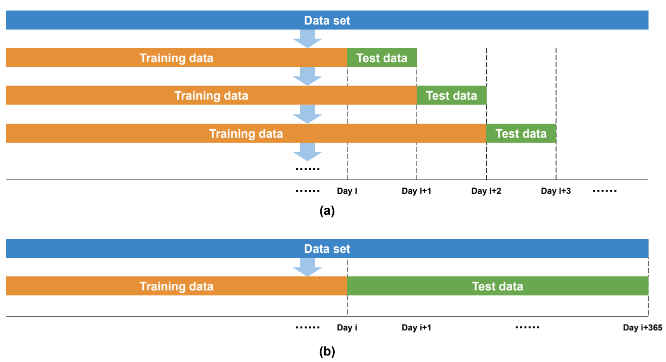

Figure 7. Day-by-day prediction schematic (a) and one-time prediction schematic (b).

IV. Results and discussion

A. Ensemble learning results

An ensemble learning technique was applied to each feature set to generate ensemble predictions. Table II presents the prediction accuracy and the computation time of the proposed LSTM and CNN-LSTM models. According to Table II, the CNN-LSTM only has half the computation time of the LSTM for same training times of ensemble learning, while still boasts higher prediction accuracy over the LSTM using less computation time.

TABLE II. Prediction accuracy and computation time comparison.

Model	Computation time	Ensemble times	R^2	RMSE
LSTM	59 min	15	0.5782	7.062
LSTM	120 min	30	0.5821	7.028
CNN-LSTM	**60 min**	**30**	**0.5825**	**7.027**
CNN-LSTM	40 min	20	0.5824	7.031

The prediction results utilizing all the features using the day-by-day prediction approach is depicted in Fig. 8. It is noteworthy from Fig. 8 that each training iteration results in a unique individual prediction on the test set, underscoring the inherent uncertainty in the neural network training process. The proposed ensemble learning approach effectively reduces the variability inherent in individual model predictions. Although some individual predictions may diverge markedly from the actual electricity spot prices, the ensemble method, described in (1), averages these forecasts to produce a more reliable final prediction. The model is capable of predicting zero prices, indicating the validity of the ”policy-versus-policy” zero prices forecasting strategy. The ensemble learning metrics for the day-by-day prediction approach using all the proposed features is illustrated in Table III. By using the day-by-day prediction approach, the prediction accuracy is much improved compared with the one-time prediction approach.

TABLE III. Ensemble learning metrics for the day-by-day prediction approach using all proposed features.

Metrics	
RMSE	R^2
5.66	0.729

B. Implications for EPF’s confidence interval

In Fig. 8, it is noteworthy that when the ensemble learning prediction accuracy is high, the 30 individual predictions tend to highly overlap each other and also demonstrate high prediction accuracy, as shown for the period 2022.05.09-2022.05.14 in Fig. 8(b). Conversely, when the ensemble learning fails to predict the actual value accurately, the 30 individual predictions tend to diverge from each other without overlaping. The standard deviation of the 30 individual predictions at the same time point is calculated and used to compute the Person correlation efficient with the ensemble learning prediction error at the same time point. The correlation efficient value is 0.462, indicating a moderate correlation. By utilizing the above-mentioned phenomenon, a novel confidence interval estimation method for EPF can be developed in our future work.

V. Conclusions and future work

This study has proposed an innovative EPF framework that utilizes multimodal data augmented by an ensemble learning technique. The CNN-LSTM model is superior over the LSTM model in both prediction accuracy and computation time. The logarithm transform of the pre-processing for the electricity spot price data has been shown crucial for EPF in the Japan electricity spot market. A ”policy-versus-policy” strategy has been proposed to solve the zero-inflated regression problem, which halfs the computation time compared with traditional two-stage method. By using the day-by-day prediction approach, the ensemble learning method achieved achieved a RMSE and (R^2) of 5.66 JPY/kWh and 0.728 over the test range of the full year 2022. An implication for a novel estimation method of the EPF’s confidence interval using the ensemble learning approach has been proposed.

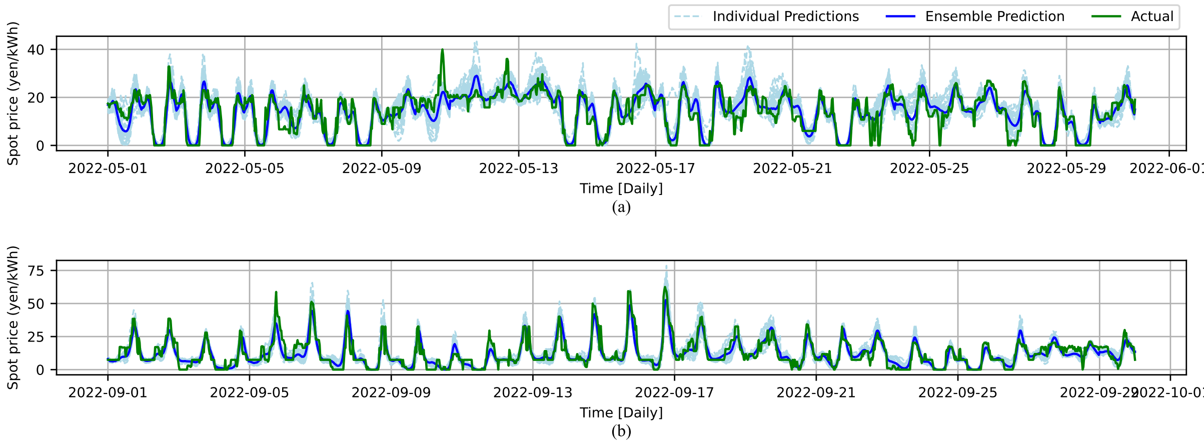

Figure 8. Individual and ensemble predictions for the test range of May and September in 2022, using all the proposed features and day-by-day prediction approach.

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