Intelligent Road Icing Early Warning System Based On Machine Learning

Rao Zhongyang, *Member, IAENG*, Feng Chunyuan, Liu Wenjiang

Abstract—**In the winter seasons, road icing is amongst the most significant threats towards road safety, which is considered as a super dangerous weather condition. This study aims to optimize road deicing predictions using machine learning (ML) techniques. By collecting data from sensors including pavement temperature (PT), pavement friction coefficient (PFC), pavement condition (PC), thickness of water film (TWF), freezing temperature, ice content (IC) and ice warning value (IWV), we analyzed crucial parameters affecting road deicing – road surface temperature. Predicting pavement icing (PI) is critical in the transportation field. To achieve this, we utilized the Long Short-Term Memory (LSTM) ML model to estimate icing conditions on the 2nd Ring South Road in Jinan, China. By considering relevant parameters of the road surface within a specific timeframe, we attempted to forecast road temperature, providing a novel approach for predicting road icing. Experimental results demonstrated the model's ability to accurately predict icing conditions. Furthermore, by utilizing observed data from the current road condition, we were able to precisely predict road temperature and thereby forecast road icing occurrences.**

Index Terms—**Road Icing Predicting, Machine Learning (ML), Road Surface Temperature, Long Short-Term Memory (LSTM)**

I. INTRODUCTION

IN the modern society, transportation functions essentially to promote the social economies [1]. Modern transportation mainly includes railway transportation, highway transportation, waterway transportation, air transportation and Pipeline transport. In China, road transportation accounts for approximately three-quarters of all transportation methods. However, statistics show that road traffic accidents result in greater economic losses and casualties compared to other disasters like floods and fires [2]. One major contributing factor to these accidents is road icing, which significantly reduces frictions between road surfaces and tires, making it difficult for automobiles to brake and increasing the risk of slipping. Pedestrians are also vulnerable to slipping and falling on icy roads. In fact, road icing is responsible for 10 times more accidents than non-icy road conditions[3]. T Therefore, accurately predicting the occurrence of road icing and implementing an ice road safety warning system (RSWS) has significant social impact as well as practical value.

Our icing warning system (IWS) mainly considers parameters such as road surface temperature and icing temperature, and then constructs an icing RSWS based on machine learning (ML) methods.

Organization of present article is following: Section II reviews former related results in the area; Section III introduces WS constructions; Section 4 presents data regarding our real-world dataset to compare the predicted result with the actual value; Finally, conclusions and possible developments for further work are discussed.

II. RELATED WORK

S.Saha analyzed Death Analysis Reporting System (FARS) dataset prepared by NHTSA from 1994 to 2012, which contains weather report information for each fatal accident [4]. They found that fatalities relating to adverse weather (AW) conditions were ~16% on average. The magnitude with regard to fatal crashes relating to AW was a bit higher in the winter seasons. Higher risk upon injury crashes correlated to wintry and snowy conditions because of road surface condition changes. Therefore, predicting when the road surface will freeze may decrease accident occurrence in some extent.

Early WS could monitor and forecast road icing conditions. The systems analyze correlations between road surfaces and the environment.

In 1972, a WS to monitor and deliver warning information upon snow and ice is set up in Sweden[5]. National Weather Service (NWS) in US has established a data-driven pavement information monitoring system. Based on collected meteorological data, a highway ice thickness estimation model has been constructed, and research on estimating ice thickness under different meteorological conditions has been completed[6].

Salvatore Martorina and Nicola Loglisci monitored road surface temperature through thermal mapping of major roads in the Piedmont region of Italy, thereby predicting road icing [7]. Alexander predicts and evaluates the icing conditions of road networks based upon observation data of road weather in Denmark Highway Station from 2003 to 2007, and conducts thermal mapping to improve the accuracy of the prediction[8]. Liu Mei calculated the local minimum surface temperature, air temperature, 850hPa temperature, and 700hPa

Manuscript received on April 12, 2023; accepted on February 6, 2024.

This work was funded by Project of Shandong Province Higher Educational Science and Technology Program (no. J15LN13), Shandong Soft Science Research Project (no. 2016RKB01453), Program of Science and Technology Development of Ji'nan (no. 20181005) and PhD Research Startup Foundation of Shandong Jiaotong University.

Zhongyang Rao is a full professor and a member of Shandong Teaching Steering Committee in Shandong Jiaotong University, Jinan, Shandong Province, China. (corresponding author to provide phone: 086-0531-8068-6720; fax: 086-0531-8068-6720; e-mail: raozhongyang@sdjtu.edu.cn).

Chunyuan Feng is an Associate Professor of Shandong Jiaotong University, Jinan, Shandong Province, China. (e-mail: fengchunyuan@sdjtu.edu.cn).

Liu Wenjiang is a full professor of Shandong Jiaotong University, Jinan, Shandong Province, China. (e-mail: liuwenjiang@sohu.com).

temperature during precipitation in Nanjing, and concluded that there are differences in temperature requirements for icing conditions due to different precipitation properties. He proposed the concept of using temperature for ice prediction, which indirectly predicts whether the road surface will freeze[9]. Lei Jianjun proposed a support vector machine (SVM) integrated road icing prediction system. According to the meteorological data of Wuhan and Shiyan from 1980 to 2006, 12 meteorological factors related to road icing were selected to establish a model. The feasibility of the model was verified by comparing the case data of 2007 and 2008 [10]. For predicting bridge pavement temperature (PT), linear regression and five layer hidden layer classical BP neural network (NN) regression models were validated [11]. To address the high cost and poor real-time performance of existing ice monitoring methods, a fusion detection method based on images is proposed [12]. To prevent traffic congestion caused by road freezing, a system was developed to forecast road freezing based upon freezing generation modules utilizing weather forecast data [13].

Despite the fact that these approaches possess some ice alerting and surveillance abilities, they are incapable of foreseeing forthcoming ice circumstances. To prevent severe vehicular incidents resulting from road icing, it is imperative to devise a precise and dependable system for detecting and prophesying road icing and surface temperature, employed for deicing in crucial areas. Deicing has gradually gained acceptance and implementation among North American highway authorities as a proactive strategy for ensuring winter driver safety[14].

In our system, we predict approximately when the road will freeze and spray snow melting agents in advance.

III. Construction Of Icing Forecasting System

In this section, a brief introduction of the ML techniques used is given. At the same time, acquiring relevant data is introduced.

A. *ML Techniques*

The system will employ ML techniques known as Long Short-Term Memory (LSTM), which belongs to Recurrent NN (RNN) method. It has many applications [15-18].

Fig.1 illustrates the basic architecture of an LSTM model with a hidden LSTM layer unfolded in time. By incorporating information in prior into the learning procedures regarding the current hidden layer, LSTM could learn efficiently from time series data. This optimization enables efficient learning from the given data.

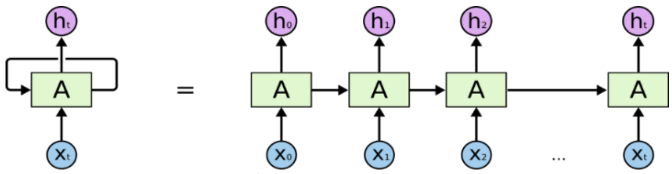

Fig. 1. LSTM system

Fundamental LSTM network consists of LSTM memory blocks that include a memory cell (c_t) and 3 gates: input (i_t), forget (f_t) and output gates (o_t). This structure can be visualized in Fig.2.

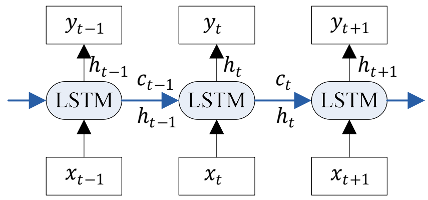

Fig. 2. Basic LSTM having 1 hidden layer unfolded in time

In short, LSTM greatly enhances the ability to capture and retain important information for the desired function. It outperforms basic RNN in terms of convergence performance. Unlike RNN which has only one function, LSTM has multiple functions to accomplish its task.

Fig.3 demonstrates correlation between LSTM functions. Outputs in each step are computed following equations (1)-(6):

$$f_t = g(W_f \cdot x_t + U_f \cdot h_{t-1} + b_f) \qquad (1)$$

$$i_t = g(W_i \cdot x_t + U_i \cdot h_{t-1} + b_i) \qquad (2)$$

$$k_t = \tanh(W_k \cdot x_t + U_k \cdot h_{t-1} + b_k) \qquad (3)$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes k_t) \qquad (4)$$

$$o_t = g(W_o \cdot x_t + U_o \cdot h_{t-1} + b_o) \qquad (5)$$

$$h_t = o_t \otimes \tanh(c_t) \qquad (6)$$

Here x_t is input vector at t. g is activation function employing ReLU or Sigmoid. U and W are weight matrices and b is bias vector. c_t and h_t are cell state and output vectors at t. $\otimes$ denotes element-wise vector multiplication. Sum of f_t serves to learn from known information to get new information.

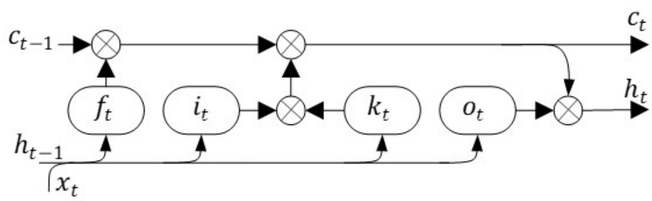

Fig. 3. Basic LSTM having 1 hidden layer unfolded in time

Equations (1)-(6) consist of formulas to compute f_t, i_t and o_t gates at t. The 3 gates receive inputs x_t and h_{t-1}, which multiplied weight matrices. Resulting products are summed up with bias term and passed through sigmoid function. The gate outputs lie within the range of 0 to 1, where an output close to 0 informs a closed gate that rejects information. Conversely, an output close to 1 signifies fully accepting the information. Therefore, the flow of information is regulated by these gates, In other words, they function essentially to determine h_t and c_t values, which serve as the primary computational components within LSTM memory blocks.

B. *Data Acquisition*

Pavement icing (PI) results from a complex interplay of various factors. The process of ice formation and melting is dynamic and closely linked to time. Hence, it is crucial to gather meteorological information in real-time, including atmospheric temperature, humidity, road surface temperature, and road conditions.

In the system, collecting data such as PT, freezing temperature, PFC, TWF, IC, PC and IWV are captured. We extracted data from some locations on 2nd ring south elevated road in Ji'nan, China ('the Road' in the following main text). Sensor installation is shown in Fig.4. In this system, sensors are installed on the road surface at critical locations.

Fig. 4. Data sensor installation of the road

Fig.5 is the data of second ring south elevated road of Ji'nan, China. The date time of the data is from 12/5/2016 to 12/26/2016.

C. Icing Forecasting System

Fig.6 shows the optimized icing forecasting system utilizing LSTM. The observation data is first normalized, and then inputted into the LSTM. Subsequently, a dense layer follows LSTM hidden layer. The dense output layer is responsible to generate the predictions.

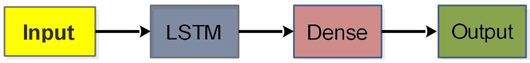

Fig.6. PI forecasting system

Inputs of the system are sensor observations, i.e., $S=\{s_1,s_2,...,s_t,...,s_N\}$, which denote all sensor observations. Every observation s_t produces data at each slot t. In the problem, every observation s_t has 7 data points at t, represented by $x_i(t), i=1,2,...,7$. $s(t)=[x_1(t),x_2,...,x_7(t)]$ contains outcome observation regarding all sensors at t. Likewise, $\hat{x}_i(t+1)$ represents observation i prediction at $t+1$. $\hat{s}(t+1)=[\hat{x}_1(t+1),\hat{x}_2(t+1),...,\hat{x}_7(t+1)]$ (same size as $s(t)$) contains all observation predictions .

The problem is: all sensor observations before t are utilized to predict observations at $t+1$. The system has a multiple input with single step output, which is illustrated in Fig.7.

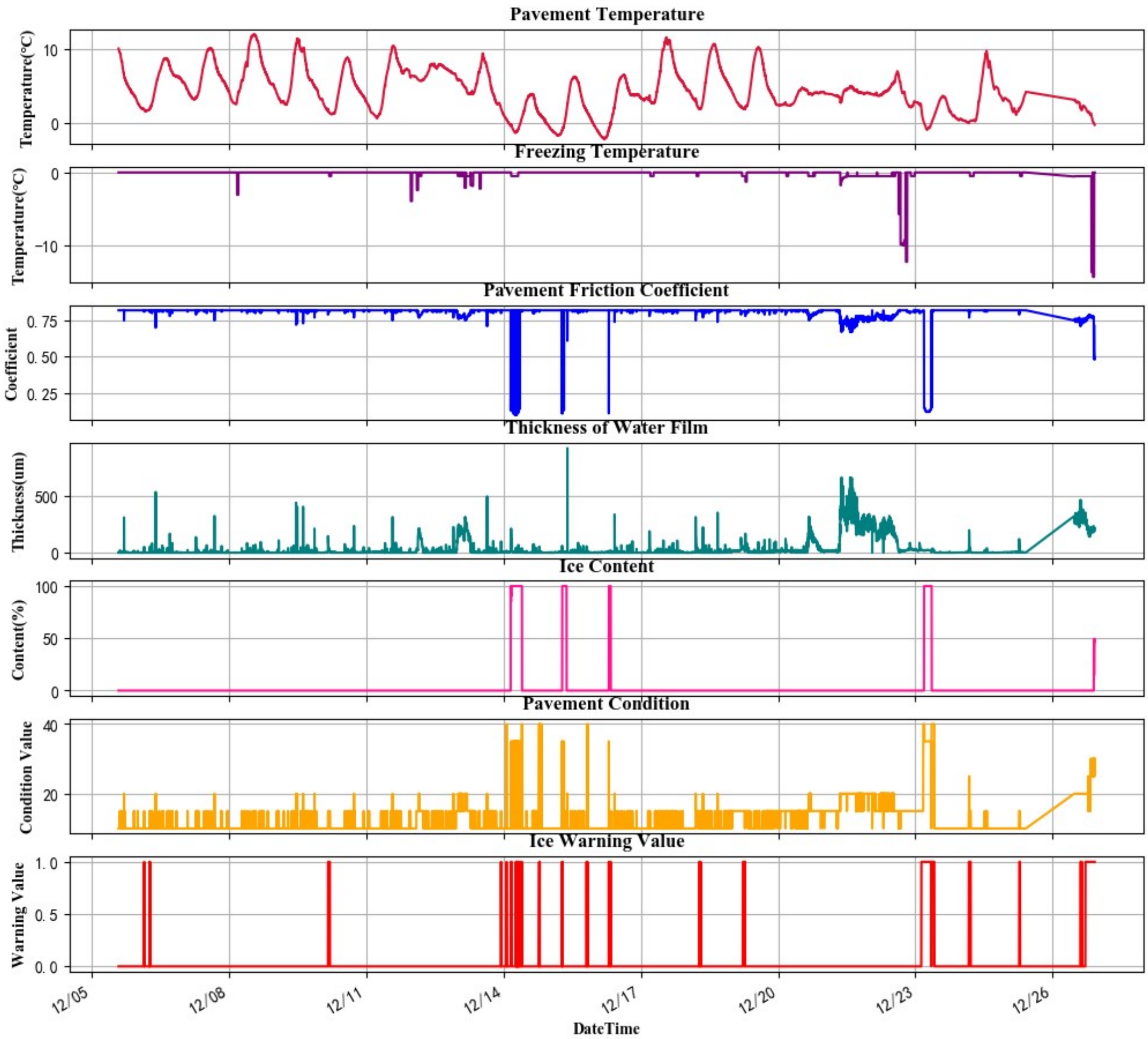

Fig.5. Data of the road

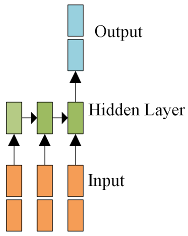

Fig.7. Multiple input and single step output

Here input $s(t)$ are the PT, freezing temperature, PFC, TWF, IC, PC and IW value, expressed by $x_1(t), x_2, ..., x_7(t)$ respectively. Output are $\hat{s}(t+1)$, which are observations at $t+1$.

Data can be previewed quickly using the pandas profiling tool, which provides an efficient way to identify highly correlated variables. Various correlation matrices, such as Spearman, Pearson, and Kendall, are available for analysis. Fig.8 displays the Spearman matrix.

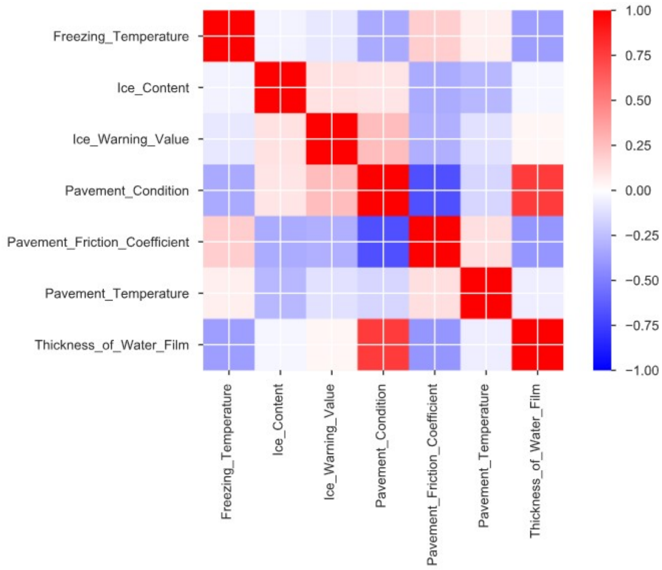

Fig.8. Matrix of Spearman

The training process for PI forecasting consists of following stages: data preprocessing, data separation, model training, and model verification.

D. Data Processing

Normalization is a process that adjusts the data range to be between 0 and 1. To achieve this, it is necessary to accurately determine or estimate maximal and minimal observable values. Fig.9 displays the normalized inputs of the PI forecasting system. The data preprocessing step involves data normalization. This step uses following equation to achieve normalization process:

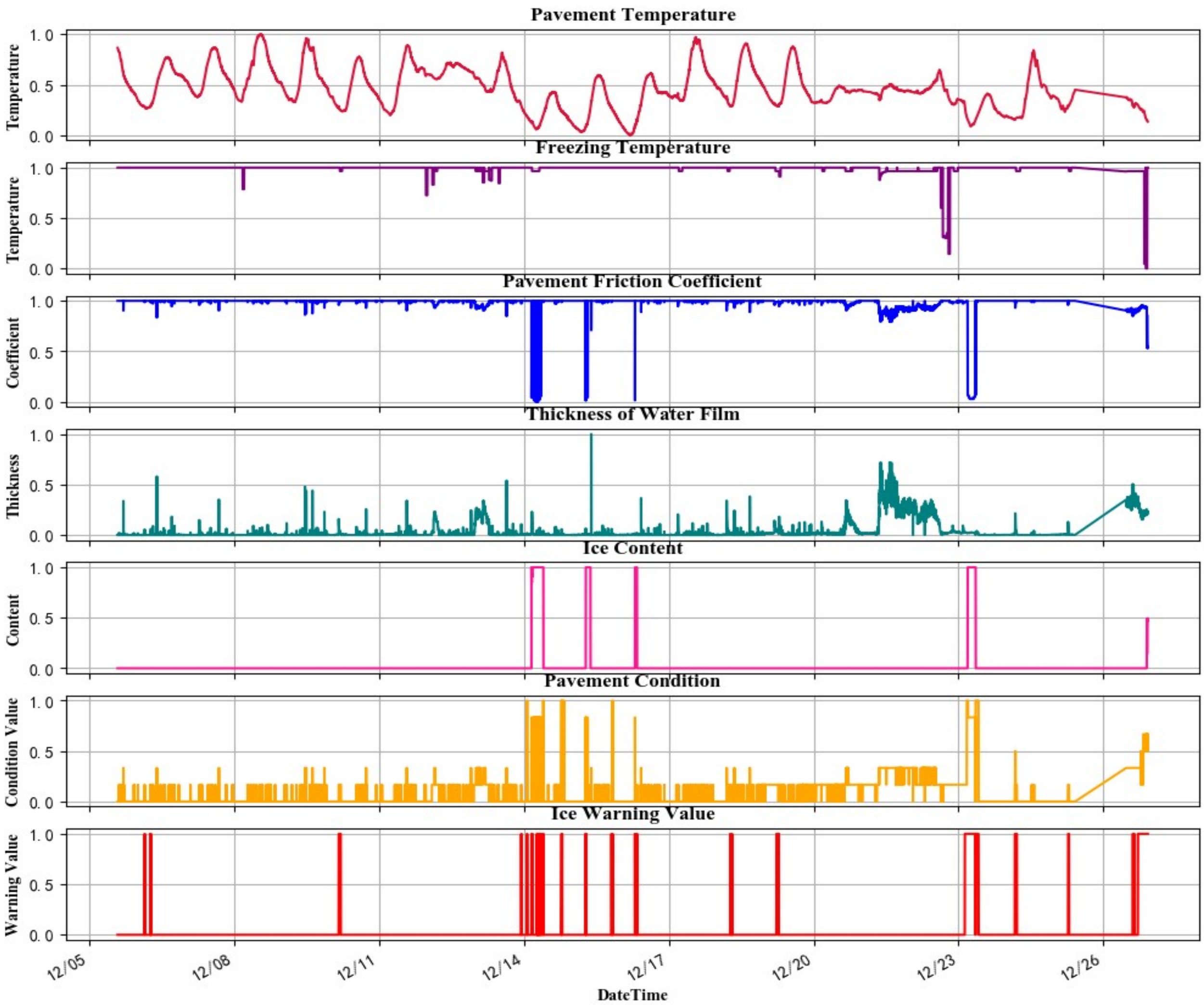

Fig.9. Normalized data of Second Ring South Elevated Road

$$x_1^*(t) = \frac{x_1(t) - x_{1\min}}{x_{1\max} - x_{1\min}} \tag{7}$$

The minimal and maximal $x_1(t)$ values can be denoted as $x_{1\min}$ and $x_{1\max}$, respectively. To gain normalized dataset $\{s_1^*, s_2^*, ..., s_n^*\}$, we use the formula (7). Here $s_t^* = [x_1^*(t), x_2^*(t), ..., x_7^*(t)]$ represents an individual observation in the data series.

E. Data Separation and Model Training

Data separation involves dividing dataset to training and testing data. We designate data from the first 10 days as the training set, while the data from the next 10 days serve as the testing data.

To ensure proper functioning of our network, the first hidden layer needs to specify the expected number of inputs, which determines the input layer shape. The input data are three-fold, organized in the following order: samples, time steps, and features. In this context, samples refer to the data rows, time steps represent past observations for a particular feature, and features correspond to data columns.

We have set the following parameters for the dimensions: samples=50, time step=1, and number of features=7. Once the network is defined, it needs to be compiled. Compilation involves transforming the sequential layers into a series of matrix transforms that can be executed efficiently. During compilation, certain parameters must be specified based on the training network. This includes selecting optimization algorithm and loss function to be used. In our model, we have chosen the adaptive moment estimation (ADAM) algorithm and mean absolute error (MAE) loss function.

When the network is compiled, it could be fitted *y* adjusting the weights based on training data. For successful fitting, training data needs to be provided in the form of an input pattern matrix **X** and a corresponding output array *y*. The network is trained utilizing back propagation through time algorithm, which is optimized as the optimization algorithm and loss function that specified during compilation. Example of a fitting network could be demonstrated by: model.fit(**X**, *y*, batch_size=70, epochs=25).

Once model has been trained, it is capable of estimating additional sequences. Model validation is established using testing dataset. PI forecast and real values of testing data are the same, while the forecast temperature and real values are provided in Fig.10.

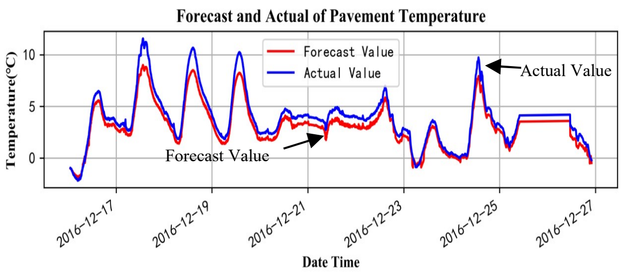

Fig.10. Forecast and actual value of pavement temperature

IV. Experiments

We collected two sets of forecast data The first set covers the period from 12/29/2016 to 12/30/2016 at a specific location. The second set covers the period from 12/5/2016 to 12/26/2016 at a different location.

The forecast and real values of PI warning on the same position are the same. Meanwhile, Figure 11 displays the forecasted temperature values at the same position. It is worth noting that both figures highlight the comparison between the forecasted values and the corresponding actual values.

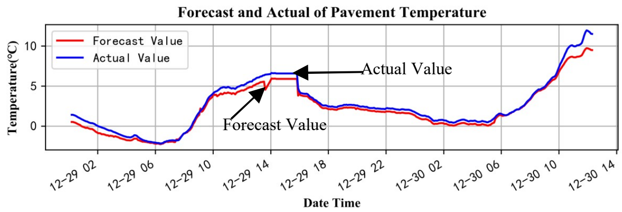

Fig.11. Forecast and real PT on same position

The forecast and real value of PI warning are the same, and temperature on other various positions are illustrated in Fig.12.

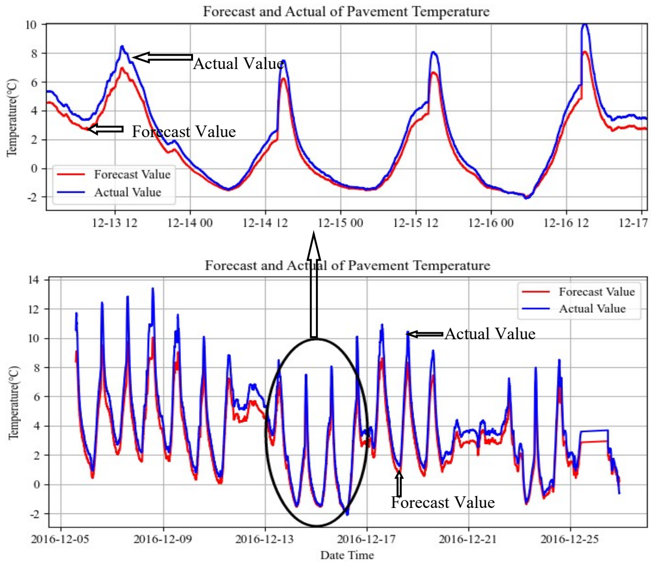

Fig.12. Forecast and real PT on different position

The criteria to measure experiment performance are Root Mean Square Errors (RMSEs) between real and forecast PT values:

$$y_{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{8}$$

Where y_i and $\hat{y}_i$ are real and forecast PT values, respectively.

RMSE results are in Table 1. The RMSE of data on different position is 0.433℃.

TABLE 1 RMSE Between Real And Forecast PT Values

Date	12/17-12/26	12/29-12/30	12/17 - 12/30
Data	testing data on same position	data on same position	data on different position
RMSE	0.706	0.587	0.433

The PI warning is very precise. And from Fig.10, forecast PT is concordant to real values. To verify the model parameter accuracies, forecast and real PI warning and PT values are compared. PI warning of the forecast and real values are the same. The results show that the model could be applied to the Road.

Fig.13 shows the contrast in road conditions when utilizing an early WS and automatic antifreeze spraying. The top image represents the absence of early warnings and subsequent antifreeze spraying, while the bottom image highlights the effectiveness of early warnings combined with automatic antifreeze spraying. This figure convincingly illustrates that the use of antifreeze during early warnings significantly reduces the occurrence of traffic accidents.

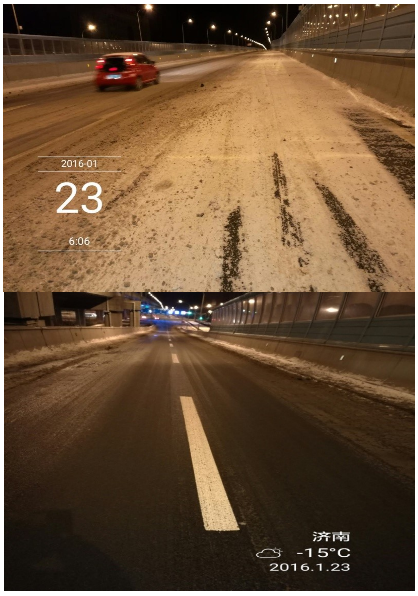

Fig.13. Comparison of road conditions before and after using an early WS and automatically spraying antifreeze

V. Conclusions

In current article, we employed LSTM to anticipate PI warning. Findings demonstrate that the model is capable of accurately foretelling PI warning. Building upon our investigation and approach, it has the potential to forecast the temperature of the pavement. Consequently, it can diminish the frequency of traffic mishaps and enhance traffic control within our nation.

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