Research Article

Prediction of highway pavement surface condition based on meteorological parameters using Deep Learning Method

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DOI: 10.51513/jitsa.1152377

Abstract: The condition of the pavement surface on highways is an important factor in ensuring traffic safety. The condition of the road pavements varies according to the climatic conditions of the road. To record the variability of road pavements according to meteorological factors, both sensors placed in the pavement and road meteorology information stations are installed on the roadsides. Within the scope of intelligent transportation systems, the establishment of road management information systems and the status of the road pavement in real-time can be observed with the data obtained from the sensors. With these sensor data, the road surface condition can be estimated with different artificial intelligence methods. Thus, important information is provided for decision-makers in taking precautions according to the dry, wet, and icy road surface condition. In this study, it is purposed to estimate the road surface condition based on meteorological parameters. For this purpose, deep learning models have been developed. Air temperature (tmp), dew point temperature (dwp), wind speed (sknt), wind direction (drct), wind gust (gust), pavement sensor temperature (tfs), and pavement sensor condition (cond) parameters were used in 65966 datasets. Accuracy was used in the evaluation of deep learning models. Consequently, the evaluation, the accuracy value of the best model was determined as 0.88. In addition, accuracy, recall, precision, and F1-score values of each class were calculated for the test set of the best model.

Keywords: Intelligent transportation systems, artificial intelligence, deep learning, highway pavement, meteorological parameters

Derin Öğrenme Yöntemi kullanılarak meteorolojik parametrelere dayalı karayolu kaplama yüzey durumunun tahmini

Özet: Karayollarında yol kaplama yüzeyinin durumu trafik güvenliğinin sağlanmasında önemli bir faktördür. Yolun bulunduğu iklim koşullarına göre yol kaplamalarının durumu değişkenlik göstermektedir. Yol kaplamalarının meteorolojik faktörlere göre değişkenlik durumunu kayıt altına almak için hem yol kaplama içerisine yerleştirilen sensorler hem de yol kenarlarına yol meteoroloji bilgi istasyonları kurulmaktadır. Akıllı ulaşım sistemleri kapsamında yol yönetim bilgi sistemlerinin kurulması ve sensörlerden alınan veriler ile gerçek zamanlı yol kaplamasının durumu gözlenebilmektedir. Bu sensor verileri ile yol yüzey durumu farklı yapay zekâ yöntemleri ile tahmin edilebilmektedir. Böylece yol yüzey durumunun kuru, ıslak ve buzlu olmasına göre önlemlerin alınmasında karar vericiler için önemli bilgiler sunulmaktadır. Bu çalışmada, meterolojik parametelere bağlı yol yüzey durumu tahmin edilmesi amaçlanmıştır. Bu amaçla, derin öğrenme modelleri geliştirilmiştir. 65966 adet veriseti içerisinde hava sıcaklığı, çiğ noktası sıcaklığı, rüzgâr hızı, rüzgâr yönü, esinti hızı, kaplama sensör sıcaklığı ve kaplama sensör durumu parametreleri kullanılmıştır. Derin öğrenme modellerinin değerlendirilmesinde doğruluk kullanılmıştır. Yapılan değerlendirme sonucunda en iyi modelin doğruluk değeri 0.88 olarak belirlenmiştir. Ayrıca en iyi modelin test seti için her bir sınıfa ait doğruluk, duyarlılık, kesinlik ve F1-skoru değerleri hesaplanmıştır.

Keywords: Akıllı ulaşım sistemleri, yapay zeka, derin öğrenme, karayolu üstyapı, meteorolojik parametreler

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Received 03.08.2022; accepted 23.08.2022

1. Introduction

The surface condition of the road pavement on highways is one of the considerable road safety factors. Whether the pavement surface is dry, damp, wet, or covered with ice is an important factor for drivers using the road. The condition of the road pavement may change according to meteorological conditions. While the road surface may be dry in hot climate regions, the pavement surface also varies in parallel with this situation in climates with heavy rainfall. Road sensors can be used to determine the surface condition of road pavements (Alqudah and Sababha, 2017; Dudak et al., 2017). The sensors positioned on the road can record continuously depending on the pavement temperature and weather conditions. In addition, road weather stations (RWS) are located on the roadsides and automatically collect and record the meteorological conditions to which the pavement is exposed in real-time. The RWS system is equipped with a series of sensors that allow the collection of meteorological data such as air temperature, relative humidity, wind speed, precipitation type, visibility, and with the help of these sensors, data such as road surface temperature and road surface condition can be transferred to road management stations (Kocianova, 2015). In a study, Kocianova (2015) observed and predicted the condition of the road surface for smart winter road maintenance management in Slovak climate conditions by collecting data with the weather station installed on the roadside depending on meteorological conditions. According to the data collected at the RWS stations, it is thought that the traffic accidents will decrease as the necessary intervention to the pavements will affect traffic safety positively. It is important to use estimation methods to determine the condition of the pavement according to future meteorological conditions and to take the necessary precautions. As some of the estimation methods used, the statistical approach method in estimating the road surface condition (Krsmanc et al., 2013; Bouilloud et al., 2009) Machine Learning method (Liu et al., 2018; Yang et al., 2020; Molavi Nojumi et al.,2022), artificial neural network method (Xu et al., 2017; Li et al., 2022), Deep Learning method (Milad et al., 2021) have been used to predict the condition of the pavement.

This study aims to predict the state of the road surface based on road meteorological parameters with deep learning. In the study, meteorological data of the location of the road pavement from the Road Weather Information System of the Iowa Department of Transportation in the USA were used. A numerical value of 0, 1, 2, and 3 were assigned to the dry, trace moisture, wet, and ice data obtained from the sensor of the road pavement, respectively.

2. Methods

2.1. Dataset

Data from The Iowa Department of Transportation's Road Weather Information System in the USA were used to estimate the pavement surface condition (URL-1, 2022). The data set consists of meteorological parameters such as air temperature (F- tmp), dew point temperature (F- dwp), wind speed (knots- sknt), wind direction (degree N- drct) wind gust (knots-gust), pavement sensor temperature (F-tfs), and pavement sensor condition. Statistical information about the data set is given in Table 1.

Table 1. Dataset statistical parameters

	tmp	dwp	sknt	drct	gust	tfs	cond
count	65966	65966	65966	65966	65966	65966	65966
mean	49.66	40.85	7.43	194.10	10.70	58.57	0.44
std	21.96	20.59	4.97	95.65	6.83	27.08	0.93
min	-24.70	-30.28	0.00	0.00	0.00	-15.90	0.00
25%	33.62	26.10	3.50	130.00	5.20	37.60	0.00
50%	51.62	41.90	7.00	185.00	9.72	58.82	0.00
75%	67.10	58.82	10.40	285.00	14.80	76.60	0.00
max	95.00	80.80	36.72	360.00	131.75	131.70	3.00

2.2. Deep learning

Deep learning algorithms emerged as a computer analogy of a neuron in the human brain. Deep learning is used especially for classification, recognition, and detection (Dogan and Turkoglu, 2018).

Deep learning includes very deep neural networks, typically deeper than three layers, and a class of models that attempt to hierarchically learn deep features of the input data. Firstly, it begins as unsupervised training on a network layer basis. It is then adjusted in a controlled manner. Deep learning models can become more complex and abstract from layer to layer. A deep neural network model is given in Figure 1.

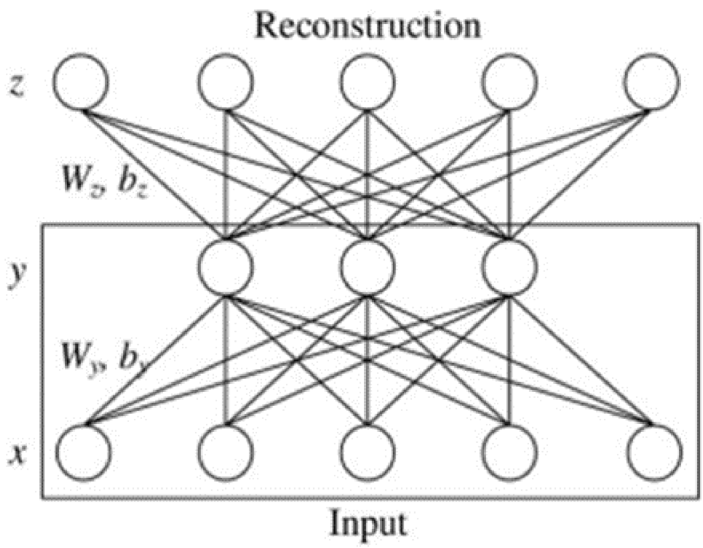

Figure 1. Deep neural network structure (Chen et al., 2014)

Figure 1 shows a single-layer deep neural network structure for the classification problem. The model learns a hidden feature 'y' from input 'x' by reconstructing it on 'z'. The corresponding parameters are displayed in the network (Chen et al., 2014).

2.3. Evaluation metrics

Accuracy (Acc) symbolizes the ratio between correctly predicted samples and all samples in the dataset (Equation 1). It is described for each confusion matrix M and takes values in the range 0-1. The accuracy value of 0 corresponds to the old classification, and 1 corresponds to the correct classification (Chicco and Jurman, 2014).

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Precision is the probability that a type is available given an estimated availability. Recall (more commonly referred to as susceptibility) is the probability that the model estimates the presence where the species is observed (Sofaer et al., 2019). Precision and recall are given in Equations 2 and 3, respectively.

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

TP represents cases where the model correctly predicts positive classes, that is true positive values, FP (false positive), cases where the model incorrectly predicts positive classes, FN (false negative) symbolizes cases where the model incorrectly predicts negative classes (Rahim et al., 2021).

F1-score is the most-used member of the F-measures parametric family, called after the parameter value β =1. The F1 score is described as the harmonic mean of precision and recall (Equation 4). An F1-score value of 0 means the model result is bad, and a 1 means that the model result is good (Chicco and Jurman, 2014).

$$\mathrm{F1-score} = 2 * \frac{\mathrm{precision}*\mathrm{recall}}{\mathrm{precision}+\mathrm{recall}} \tag{4}$$

3. Results

This study, a deep learning model was improved for pavement surface condition prediction. Meteorological dataset was used to develop the deep learning model. Before the model was developed, the relations between the variables were examined with the correlation matrix and pair plot.

The strongest correlation coefficients between the two variables were indicated as 1 positive and -1 negative correlation. The correlation matrix is given in Figure 1 to determine the relationships of the variables with each other.

Figure 2. Correlation matrix

When Figure 2 is examined, the correlation value of each variable with itself is 1 and is located on the matrix cross line. The strongest positive relationship among the variables is between air temperature and pavement surface temperature, with a correlation value of 0.93. There is also a strong positive relationship between tmp - tfs, sknt - gust, tmp - dwp, and dwp - tfs. The lowest relationship in the negative direction is between the pavement temperature and the pavement state. In Figure 3, the pair plot of the data set is given.

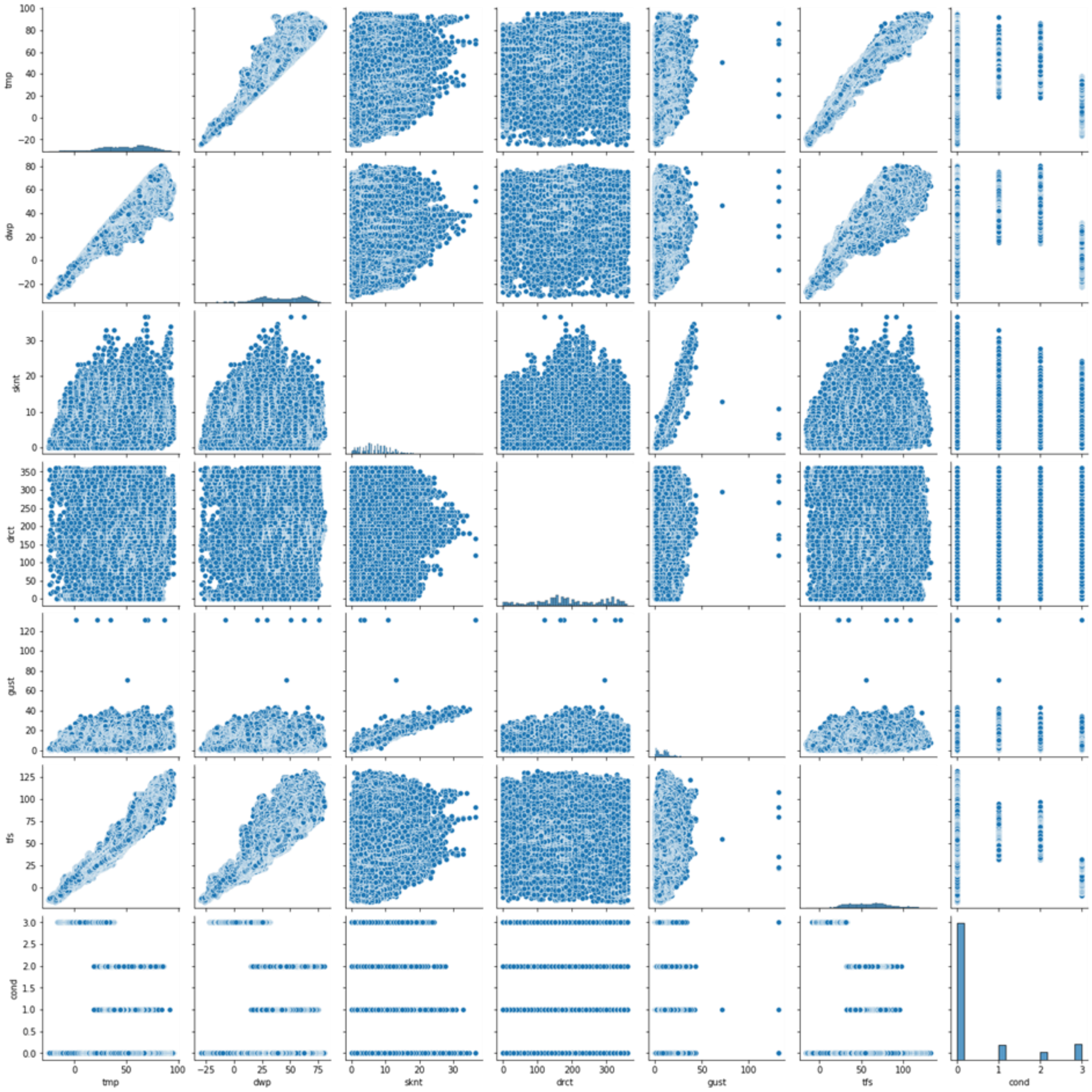

Figure 3. Pair plot of the data set

By using the variables air temperature (F), dew point temperature (F), wind speed (knots), wind direction (degree N) wind gust (knots), and pavement sensor temperature (F) as inputs, pavement sensor condition was estimated by deep learning. Dry, trace moisture, wet and ice watch data obtained from the road meteorology information station pavement status sensor were converted into numerical data as 0, 1, 2, and 3, respectively. Models were developed using the Keras library in Python environment. While developing the models, the best model was chosen by testing the number of hidden layers, the number of neurons in the hidden layers, the number of batch sizes and epochs. The accuracy value was used in the evaluation of the model result. As a result of the evaluation, the accuracy value for the test set of the best model is 0.88. The confusion matrix of the best model is given in Figure 4. In addition, accuracy, precision, recall, and F1 score were calculated for each class in the test set of the best model (Table 2).

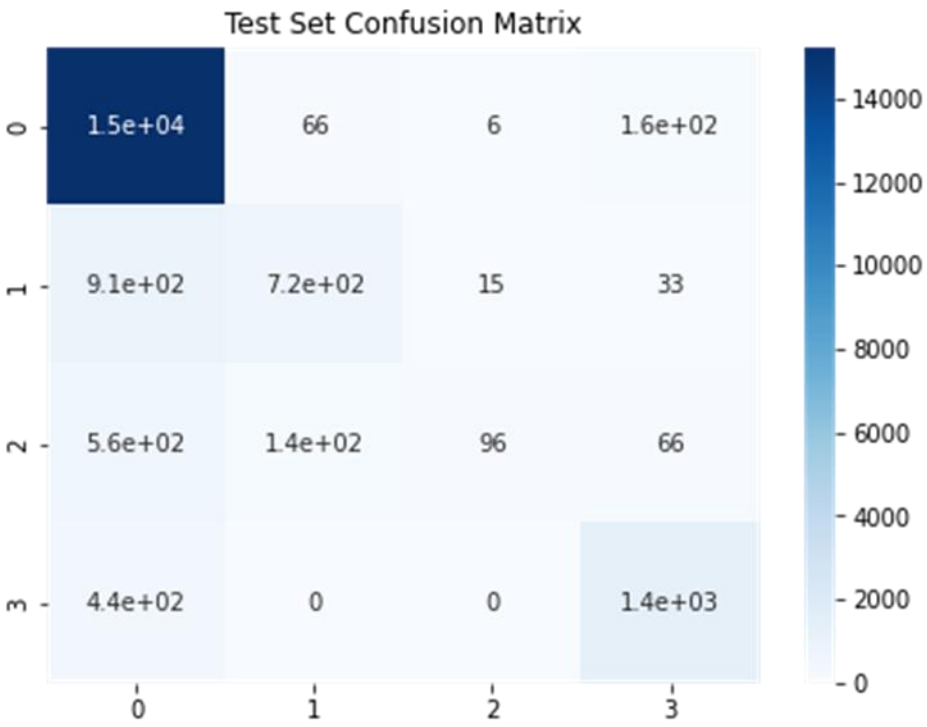

Figure 4. Confusion matrix of the test set

Table 2. Evaluation metrics for the test set

Class	Accuracy	Precision	Recall	F1-Score
0	0.89	0.99	0.89	0.93
1	0.68	0.49	0.82	0.61
2	0.71	0.42	0.96	0.59
3	0.39	0.50	0.63	0.56

When Table 2 is examined, it is seen that the 0 class shows high success according to the accuracy, precision, recall, and F1-score values.

4. Conclusion

Dry, wet and icing conditions of the highway pavement surface according to weather conditions are very important for traffic safety. Knowing the road pavement situation in these regions in advance by local authorities will reduce the risk of accidents. In recent years, developments in the field of artificial intelligence have made it possible to make high-accuracy predictions with large datasets.

In this study, pavement surface condition was estimated by deep learning meteorological parameters from The Iowa Department of Transportation's Road Weather Information System. Deep learning models were developed with gust (knots), pavement sensor temperature (F), and pavement sensor conditioning data. When the developed deep learning models were evaluated, the highest accuracy value for the test set was found to be 0.88. As a result, it is thought that deep learning models are successful in estimating pavement surface conditions. It has been seen that road pavement conditions can be predicted by using different data sets and different algorithms for future studies. It is thought that traffic accidents that may occur can be reduced by predicting road pavement situations with road management systems. In addition, it is thought that by estimating the pavement condition, road maintenance and repair operations will be more regular and the service life of the road can be used more effectively.

Researchers' Contribution Rate Statement

The contribution rates of the authors are equal.

Acknowledgment and/or disclaimers, if any

The first author (Tahsin BAYKAL) was supported by the Council of Higher Education's 100/2000 doctoral scholarship.

Conflict of Interest Statement, if any

There is no conflict of interest in the study.

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