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Towards a sustainable monitoring: A self-powered smart transportation infrastructure skin☆

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A R T I C L E I N F O

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A B S T R A C T

Sustainable monitoring of traffic using clean energy supply has always been a significant problem for engineers. In this study, we proposed a self-powered smart transportation infrastructure skin (SSTIS) as an innovative and bionic system for the traffic classification of a smart city. This system incorporated the self-powered flexible sensors with net-zero power consumption based on the Triboelectric Nanogenerator (TENG) and an intelligent analysis system based on artificial intelligence (AI). The feasibility of the SSTIS was tested using the full-scale accelerated pavement tests (APT) and the long-short term memory (LSTM) deep learning model with a vehicle axle load classification accuracy up to 89.06%. This robust SSTIS was later tested on highway and collected around 869,600 pieces of signals data. The generative adversarial networks (GAN) WGAN-GP (Wasserstein GAN - Gradient Penalty) was used for data augmentation, due to the imbalanced data of different vehicle types in actual traffic. The overall accuracy for on-road vehicle type classification improved to 81.06% using the convolutional neural network ResNet. Finally, we developed a mobile traffic signal information monitoring system based on cloud platform and Android framework, which enabled engineers to obtain the vehicle axle-load

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information mobilely. This study is the emerging design and engineering application of the self-powered flexible sensors for smart traffic monitoring, which provides a significant advance for intelligent transportation and smart cities in future.

1. Introduction

Sustainable monitoring of traffic using clean energy supply has always been a significant problem for engineers. There have been numerous studies conducted on the development of intelligent transportation monitoring and sensing systems using different sensors, including light, ultrasonic, infrared, acoustic sensors those have been widely applied in vehicle queue length estimation [1], drivers signals monitoring [2], early detection of vehicle mechanical defects [3], traffic flow acquisition [4], the evaluation of road conditions [5], bridge vibration and displacement monitoring [6], traffic vehicle tracking [7] and some other areas. Normally, these sensors may also require external power supplies that makes the long-term serving almost impossible. Moreover, many of the sensors are intrusive and usually need to be buried inside the road structures [8]. The stiffness of the sensors and the road material usually does not match, so that the deformation of the sensor and the road material is inconsistent under traffic load, resulting in possible sensor failure. Considering the characteristics of the intrusive sensors, they need to be installed in the structure to change the consistency, uniformity and continuity of the infrastructure's materials. It may further make it difficult to obtain the sensing signals with high accuracy due to its low adaptivity to the inevitable deformation of civil infrastructures under long-term service and severe environmental conditions. Overall, these external powered sensors have been widely applied for traffic monitoring purposes, including road type classification [9,10], vehicle type classification [11,12], target detection [13,14], driving behavior detection [15], traffic flow prediction [16,17], travel time prediction and planning [18,19], traffic signal control optimization [20], road traffic safety accident prediction [21,22], etc.

Considering the advantages and disadvantages of external powered sensors, they may not be suitable for the low cost and sustainable development of energy in smart transportation. In recent years, the TENG based self-powered sensors have emerged as powerful tools for long-term and distributed sensing and monitoring purposes [23–25]. Based on the tribo-electrification and the electrostatic induction effect [26], TENG directly converts mechanical stimuli into electrical signals without the need of an external power supply [27–29]. The integration of the novel TENG technology, 5 G and other Internet of Things (IoT) technology will perform the functions of efficient energy harvesting and information acquisition, providing a more intelligent and cleaner solution for the future digital smart cities [30–32]. Therefore, it is very suitable in the field of smart monitoring on transportation infrastructures, like asphalt pavements, as the TENG sensors are usually assembled with flexible materials, and thus have the characteristics of flexible, economical and stable output performance [33]. Consider the advantages of the TENG sensor, it has the potential to be used for the long-term, low-cost and non-intrusive transportation monitoring purpose. Thus, in this study, we proposed a self-powered smart transportation infrastructure skin (SSTIS) system that incorporated the TENG based thin flexible sensors that can be directly attached to the road surface and an intelligent real-time analysis system based on Artificial Intelligence (AI). The feasibility of SSTIS was first tested by Accelerated Pavement Tests (APT). The Long-Short Term Memory (LSTM) deep learning model was adopted for the data analysis. SSTIS was later tested on one section of highway near Nanjing City, China and about 869,600 pieces of vehicle signal data were collected. The Generative Adversarial Network (WGAN-GP: Wasserstein GAN - Gradient Penalty) was used for data augmentation to solve the problem of imbalanced dataset and ResNet was used for intelligent classification of the vehicle types with accuracy of 81.06%. Based on the SSTIS system, we developed a mobile traffic signal information monitoring system based on cloud platform and Android framework, which enabled engineers to obtain the vehicle axle-load information mobilely. It was discovered that the proposed intelligent self-powered flexible sensing system can assist the regular public functions, like auxiliary decision-making for automatic driving, early warning of transportation infrastructure damage, high-efficient traffic flow improvement, etc, which provides the significant advances for intelligent transportation and smart cities in future.

2. Bionic self-powered sensor

2.1. Sensor design and indoor test

The construction of SSTIS is inspired by the skin sensory system (Fig. 1a). Bionic sensors based on thin flexible TENG (Fig. 1b) can fit on the road surface, similar to the sensory part of our skin. When a vehicle passes by, the sensor is mechanically excited and generates an electrical signal via the vertical contact separation process of TENG (Fig. 1c). These signals are sent to the cloud platform and the deep learning terminal (central part) through wireless transmission (the afferent neural part) for processing, and the feedback data is sent to the user through the wireless transmission device (the efferent neural part). Basically, each sensor contained a 2 * 4 TENG array. In order to ensure that the mechanical signal must be collected when the vehicle passes by, the distance between each sensor array did not exceed 15 cm (about the width of a tire). All the sensor arrays were then connected in parallel to the signal transmission device on the roadside. For each sensor, the overall device was divided into 3 functional parts. The friction layers (power generation layer) we chose were Poly Tetra Fluoroethylene (PTFE) and nano gold particles. The conductive materials were Flexible Printed Circuit Board (FPCB) and copper. And the encapsulation layers were Polyethylene Terephthalate (PET) and rubber (Fig. 1b, d). Under this condition, we conducted some basic electrical performance tests on the sensor. Single sensor can reach the peak voltage of 72 V and the peak current of 5.4μA. The generator internal resistance was about 13 MΩ through the power density test (Fig. 1e, f).

2.2. Full-scale track APT test

To preliminarily test the feasibility of these sensors under the actual severe environment on the road, we also carried out in-door fatigue tests in the asphalt lab in Beijing University of Technology, China. The results showed that the sensor can withstand more than 10,000 repeated mechanical loads, which meet the requirements of the actual environmental signal acquisition conditions (Fig. 2f). In different ambient temperature tests (35–60 ℃), the sensor signals also maintained a good consistency (Fig. 2g, h ; Supplementary Fig. S1). The feasibility of SSTIS was then validated by conducting the full-scale Accelerated Pavement Tests (APT) in University of Science and Technology Beijing, China (Fig. 2a). One TENG sensor with a length of 1 m was pasted and fixed on the surface of the road with 6 built-in sensing units in the sensor (Fig. 2b). The TENG sensors were sealed with the flexible rubber and attached to the road surface with epoxy resin adhesive. The APT's axle load simulation system adopted the hydraulic pressure to realize stepless loading conditions. In this test, there were four kinds of loading conditions applied (9MPa, 10MPa, 11MPa and 12 MPa), as listed in Table 1. Take Class 4 for example, the vehicle pressure is 12 MPa, Wheel No.1 and No, 2 of Axle 1 is 7650.0 kg and 8000.0 kg, respectively; wheel No. 3 and No. 4 is 8660.0 kg and 8246.7 kg, respectively; total weight is32556.7 kg and there are overally 519, 680 pieces of signals.

For each loading condition, the vehicle ran 50 circles at speeds of 7 km/h, 10 km/h, 15 km/h, 20 km/h, and 25 km/h, respectively (Fig. 2i). SSTIS can generate 8 groups of data containing vehicle information fingerprints at the same time (Fig. 2e) and send it to the cloud through 8-channel wireless transmission device for subsequent processing (Fig. 2c, d). Under the same test conditions (load and speed), the sensing data between 50 cycle tests has good stability and repeatability, which is very important for the subsequent acquisition of data on the actual road (Fig. 2j).

There were overall 16 groups of tests and each group of the test took about 1 h. Different loading conditions were applied by the hydraulic pump station to simulate four different axle load conditions. And a Recursive Neural Network (RNN), namely LSTM (Long Short-Term Memory), was used to extract, learn and analyze the signal features of around 2,140,160 pieces of signals data. The model included 6 LSTM classifiers, and consisted of two LSTM layers with a cell size of 128. The sensor comprised of 8 built-in sensing units. Each time the test vehicle passed through the sensor, a signal matrix with 2560 rows and 8 columns was generated. Thus, in LSTM model, the input time point of the model was 2560, and the data channel of each time point was 8. The Dropout regularization operation was used after each LSTM layer to prevent over-fitting. In order to optimize the model performance, L2 regularization term was added to the Categorical Crossentropy loss function, and the regularization parameter $\beta = 0.0015$. The model used Adam [34] optimizer to continuously update the weight parameters. The batch size was 128 and the learning rate of the model was set at 0.001. Finally, this model reached a satisfactory accuracy of training set with 92.19% and test set with 89.06%, respectively. The full-scale accelerated pavement test results showed that the flexible TENG sensors fixed on the surface of the road can be used to monitor different vehicle loading conditions accurately.

3. Monitoring and intelligent analysis

3.1. Real traffic signals collection

A 4-day field test was carried out in the Ninggao section of National Highway 235 in Nanjing City, China. Two sensors with a spacing of 100 cm were pasted and fixed on the asphalt road surface. The package size of TENG sensors was $2.00 \times 0.3 \times 0.002$ m and the number of sensing units in each sensor was 8. The test used the mixing epoxy resin to paste the sensors to the road surface. The sensors were connected to the roadside data acquisition platform using a cable, and later transmitted to the laptop through the Bluetooth wireless connection, which can be replaced by a commercial 5 G wireless connection in future studies.

3.2. Signal data pre-processing

To train the data using the deep learning methods, we first labeled the sensor data into the specific vehicle types according to vehicle classification of *the Federal Highway Administration (FHWA) Traffic*

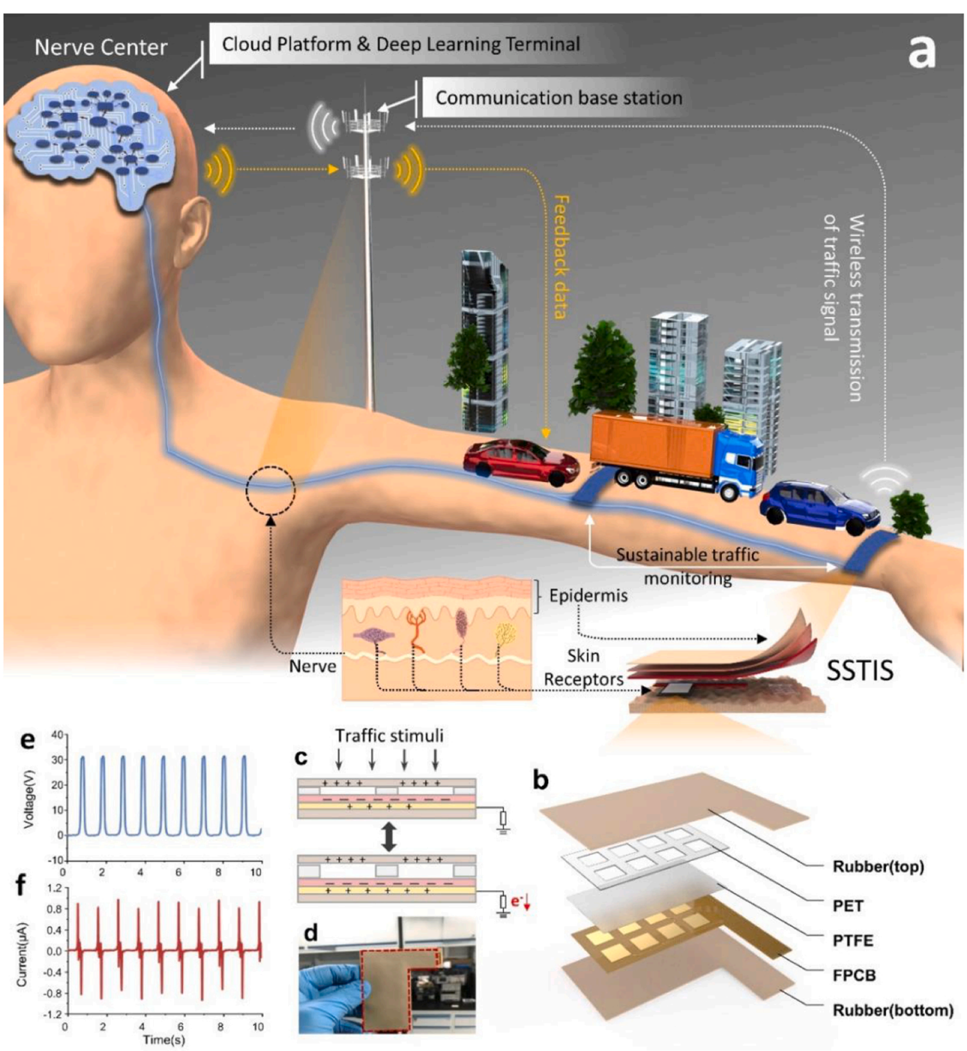

Fig. 1. A self-powered smart transportation infrastructure skin (SSTIS) system in smart cities. a. The TENG sensors were pasted and fixed on the road surface to construct the smart transportation infrastructure skin system. The sensors collected vehicle signals, and then these data can be transmitted by wireless system (4 G/5 G/6 G) to the brain of smart cities. The brain used Artificial Intelligence-based methods, like deep learning approaches, to process, analyze, and deliver the real-time traffic information to the road users. b. Schematic diagram of TENG structure. The materials used from top to bottom were Rubber (top), PET, PTFE, FPCB and Rubber (bottom). c. The working mechanism of TENG sensor. Single-electrode mode TENG was used in this study. Two different materials of the sensor (Rubber and PTFE) carried equal amounts of dissimilar charges through mutual friction. The device completed the compression-release cycle under external force conditions. When the distance between the two materials changed, an induced electric field was generated on the outside of the bottom friction layer (PTFE layer). When the sensing layer was connected to the earth, an alternating current was generated. d. The image of bionic sensor array package based on TENG. e. f. Performance characterization results of the TENG sensor, which are open-circuit voltage (blue) and short-circuit current (red).

Monitoring Guide (TMG) [35] in USA and *Motor vehicles and trailers-Types-Terms and definitions (GB/T3730. 1–2011)* [36]. A video camera was set near the TENG sensors to record the passing vehicles, and the experienced transportation technicians manually labeled the signals by comparing the video and the collected TENG sensor signals. Specifically, according to the number of vehicle axles, the axle load spectrum was categorized as passenger cars or two-axle, four-tire and single-unit vehicles, two-axle, six-tire and single-unit vehicles, three-axle single-unit trucks, four or fewer axle single-trailer trucks and six or more axle single-trailer trucks. The classification results are shown in Fig. 3a and Table 2.

In order to display the vehicle axle loads more clearly, where the vehicle signals were firstly visualized and benchmarked. For each TENG sensor, it consisted of 8 units and the collected signal was a matrix with 8 columns and multiple rows, representing the passing of vehicles over the sensors in a time series. The sampling frequency of the sensor is 256 Hz, and 400 rows correspond to 1.56 s, which is long enough to represent a full passing of vehicles. Thus, 400 rows were truncated from the total data to represent a specific vehicle passing over the sensors, constructing a 400 by 8 matrix. The collected signals were then pre-processed before the deep learning studies. Firstly, normalize the data and convert the signal matrices of vehicles into images. In this study, the minimum value of each sample was normalized to 0, the maximum value was normalized to 255, and the other values were normalized according to Eq. (1).

$$OutImage_{piexl}[i,j] = \left\lfloor \frac{(y_{max} - y_{min}) \times (InImage_{piexl}[i,j] - x_{min})}{x_{max} - x_{min}} + y_{min} \right\rfloor \tag{1}$$

where: i represents the matric number of row; j represents the matrix number of the column; $\mathrm{OutImage}_{\mathrm{piexl}}[i,j]$ is the value after normalization transformation operation; $y_{max} = 255$; $y_{min} = 0$; $InImage_{piexl}[i,j]$ is the current value of the input vehicle signal data matrix; $x_{max}$is the maximum value; and x_{min} is the minimum value.

The key features of a raw vehicle signal, present with a 400 by 8 matrix, are unclear. Thus, the column data of each sensing unit was replicated 50 times and the signal data for each axle load vehicle was transformed into a 400 × 400 square matrix, as shown in Fig. 3b.

It is noticed that there exist system noises in each unit of sensors, resulting from (1) inconsistent performance caused by manual fabrication of TENG sensors; (2) unevenness in road surface; (3) signal noise caused by real environment. The signal noise of each unit is different, which results in the difficulties in identifying the signal image features. To solve this problem, one sensing unit (where the fourth unit was chosen in this study) was randomly taken as the standard to conduct the benchmark operation, according to Eq. (2). First, calculate the difference value between the median value of each column and the median value of the standard column. Then, subtract each unit value with the difference. The typical image of vehicle signals after benchmarking is

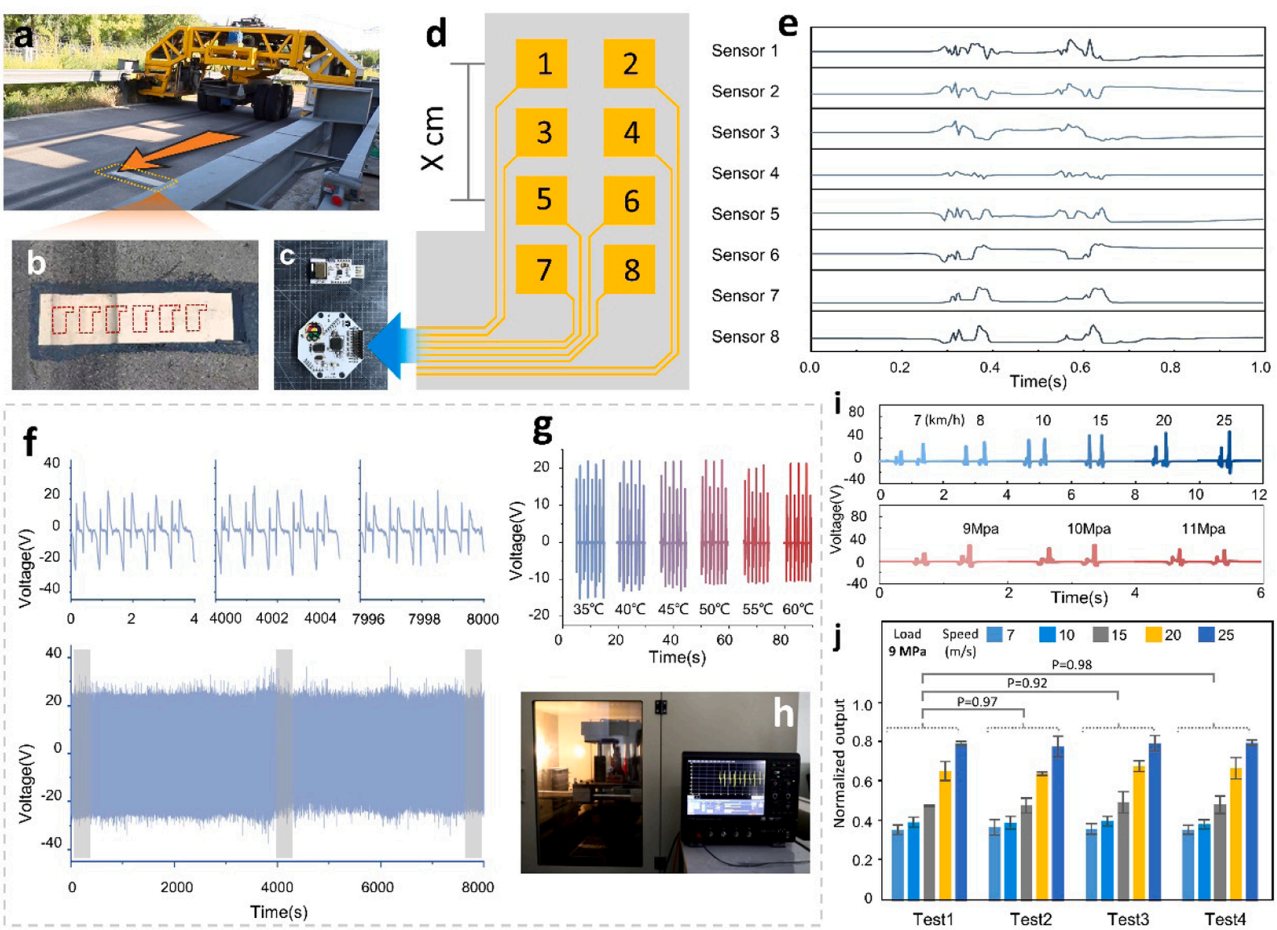

Fig. 2. Tests on the SSTIS. a. The image of APT experimental device. b. The image of the sensor skin. c. Bluetooth module. d. e. 8 groups of real-time vehicle signal information generated by TENG sensors. f. The results of in-door fatigue tests in the lab. The sensor demonstrated a stable output performance in the fatigue test after over 10,000 cycles. g. The results of ambient temperature tests. The TENG sensors outputted the stable voltage result as temperature changed continually. h. Detecting instrument of the in-door fatigue test. i. APT test results. The output change results of the TENG bionic sensor array varies with speed and pressure conditions. j. Normalization output of the TENG sensing data in 50 cycle tests.

presented in Fig. 3b.

$$OutImage_{piexl}[i,\quad j] = \quad InImage_{piexl}[i,\quad j] - (InImage_{piexl}[j]_{median} - InImage_{piexl}[std]_{median} \quad) \tag{2}$$

where $OutImage_{piexl}[i,j]$ is the value after benchmark operation; $InImage_{piexl}[i,j]$ is the median value of column j of the input vehicle signal data matrix; $InImage_{piexl}[std]_{median}$ is the median value of the standard column of a vehicle signal data; and the meanings of other symbols are the same as above.

3.3. Deep learning studies

Then, deep learning methods were used for vehicle axle load identification and classification of the five categories. The whole computation of WGAN-GP model was conducted on a desktop workstation (CPU: Intel Xeon multi-core CPUs; GPU: NVIDIA Quadro P4000, 64 GB of RAM), based on deep learning framework Pytorch 1.0.7. The ResNet-50 classification model was based on a deep learning framework developed by Google called TensorFlow 2.0, using the same computing workstation. The sever of the cloud control platform was deployed using Python programming language in Pycharm and the front-end website was based on a framework VUE in Webstorm on the same computing workstation. The Android application was installed on a 5 G smartphone (Version: Vivo Pro5G, V1916A; CPU: Snapdragon 855Plus, eight-core, 2.96 GHz).

One problem arised in the study was that compared with the other two types of axle load conditions, the quantities of two-axle, six-tire and single-unit vehicles, three-axle single-unit trucks and four or fewer axle single-trailer trucks samples were very small, where it reflected the real traffic situation (Table 2). In deep learning, the imbalance between sample sizes may result in poor computation performance. The used convolutional neural network (CNN) ResNet-50 model was employed with 60% training data, 20% validation data and 20% testing data, and the test accuracy for the imbalanced sample dataset was 80.14%, which was not very satisfactory. To solve this problem, a widely deep data augmentation Generative Adversarial Network (WGAN-GP) [37–39] was adopted. The model consists of two competing networks, namely Generator and Discrimination (Fig. 3c). The Generator network took self-set random noise as input to generate fake images, while the latter Discrimination network was used to identify whether there was any difference between the fake data generated by the Generator and the real data. The structure of the WGAN-GP algorithm is shown in Table 3. The Generator network was a six-layer convolutional neural network. The number of kernels in each layer was [4,8], the stride was [1–3], and the padding was [0, 1, 1, 0, 1]. Batch normalization and ReLU activation functions were added behind each convolution. The Discriminator network was the reverse process, which took the output of the Generator network as the input parameter. After six times of convolution, normalization, and LeakyRelu activation operations, the output was a one-dimensional value between 0 and 1 that represented the probability of real data.

The model carried out data augmentation on 402 images of passenger cars or two-axle, four-tire and single-unit vehicles, 226 images of two-axle, six-tire and single-unit vehicles, 58 images of three-axle single-unit trucks, 108 images of four or fewer axle single-trailer trucks and 509 images of six or more axle single-unit trucks. The learning rate was 3×10^{-4}, batch size was 10 and the gradient penalty item was set as 10. The model took Adaptive Moment Estimation (Adam) gradient descent algorithm [39] to optimize the network weight continuously and iterated for one million epochs. In each epoch, the training generator performed 1 iteration and the training discriminator performed 5 iterations. Both two networks train meanwhile, adjust and optimize with each other, jointly minimize the loss value [40]. Finally, a much more balanced dataset composed of 1000 training images of each vehicle type respectively were generated. The dataset after augmentation is shown in Table 2.

Finally, we employed ResNet-50 to classify the vehicle axle load signals data (Fig. 3d). Compared with the traditional convolution layer, the ResNet network makes a breakthrough in using residual units to make the input and output of any several layers of the network realize shortcut connections, which results in faster training and a better performance [41]. The balanced dataset augmented by WGAN-GP was input into the ResNet-50 model. The model utilized Categorical Cross-entropy as the loss function and Adam as weight update optimizer to carry out a mass of parameter adjustments on 5000 training images, 438 validation images and 433 test images. The system hyper-parameters were: batch size = 64, the learning rate = 3×10^{-4} and learning rate attenuation parameter = 0.1. The default values 0.9 and 0.999 were taken for rates for the moment estimates $\beta 1$ and $\beta 2$ respectively [34]. At last, the model reached 81.06% test accuracy after 100 epochs training.

It should be noted that as the government policies restricted the field tests during the COVID-19 pandemic, we are unable to conduct more experiments and collect more actual data, and future studies will take this issue into consideration.

3.4. Analysis results and discussion

In this study, accuracy, precision, recall rate, F1-score value, confusion matrix and Receiver Operating Characteristic Curve (ROC) and Area Under ROC Curve (AUC) were further adopted to evaluate the performance results of vehicle axle load classified by the ResNet-50 (Fig. 3e and Fig. 4d-f). Fig. 4f presents the accuracy curves during training. It can be seen that the approach shows high classification performance for different vehicle types. The evaluation metrics for each axle-load vehicle are shown in Fig. 4d. It is seen that the ResNet-50 classifier is able to identify almost all the passenger cars or two-axle, four-tire and single-unit vehicles and six or more axle single-trailer trucks, where the accuracy of precision, recall and F1 score are satisfactory. For two-axle, six-tire and single-unit vehicles, three-axle single-unit trucks, four or fewer axle single-trailer trucks, the precision is 0.69, 0.72 and 0.71, recall remains 0.47, 0.74 and 0.57 and F1 score obtains 0.73, 0.67 and 0.70, respectively.

The confusion matrix [42] shows the performance of the classifier in

Table 1
Hydraulic pressure, weight and axle load types in APT test. Data obtained from the full-scale Accelerated Pavement Tests (APT) in University of Science and Technology Beijing, China on October 15th, 2019. There were four vehicle axle load types, each of which corresponded to different vehicle pressure and axle weight.

Vehicle pressure (Mpa)	Axle 1 (kg)			Axle 2 (kg)			Total Weight (kg)	Pieces of signals (pieces)
	Wheel No.1	Wheel No.2	Axle Weight	Wheel No.3	Wheel No.4	Axle Weight		
Class1 **9.0**	5600.0	5996.7	11596.7	6683.3	6383.3	13066.7	24663.3	542,720
Class2 **10.0**	6376.7	6763.3	13140.0	7396.7	7026.7	14423.3	27563.3	542,720
Class3 **11.0**	6820.0	7310.0	14130.0	7960.0	7655.0	15615.0	29745.0	535,040
Class4 **12.0**	7650.0	8000.0	15650.0	8660.0	8246.7	16906.7	32556.7	519,680

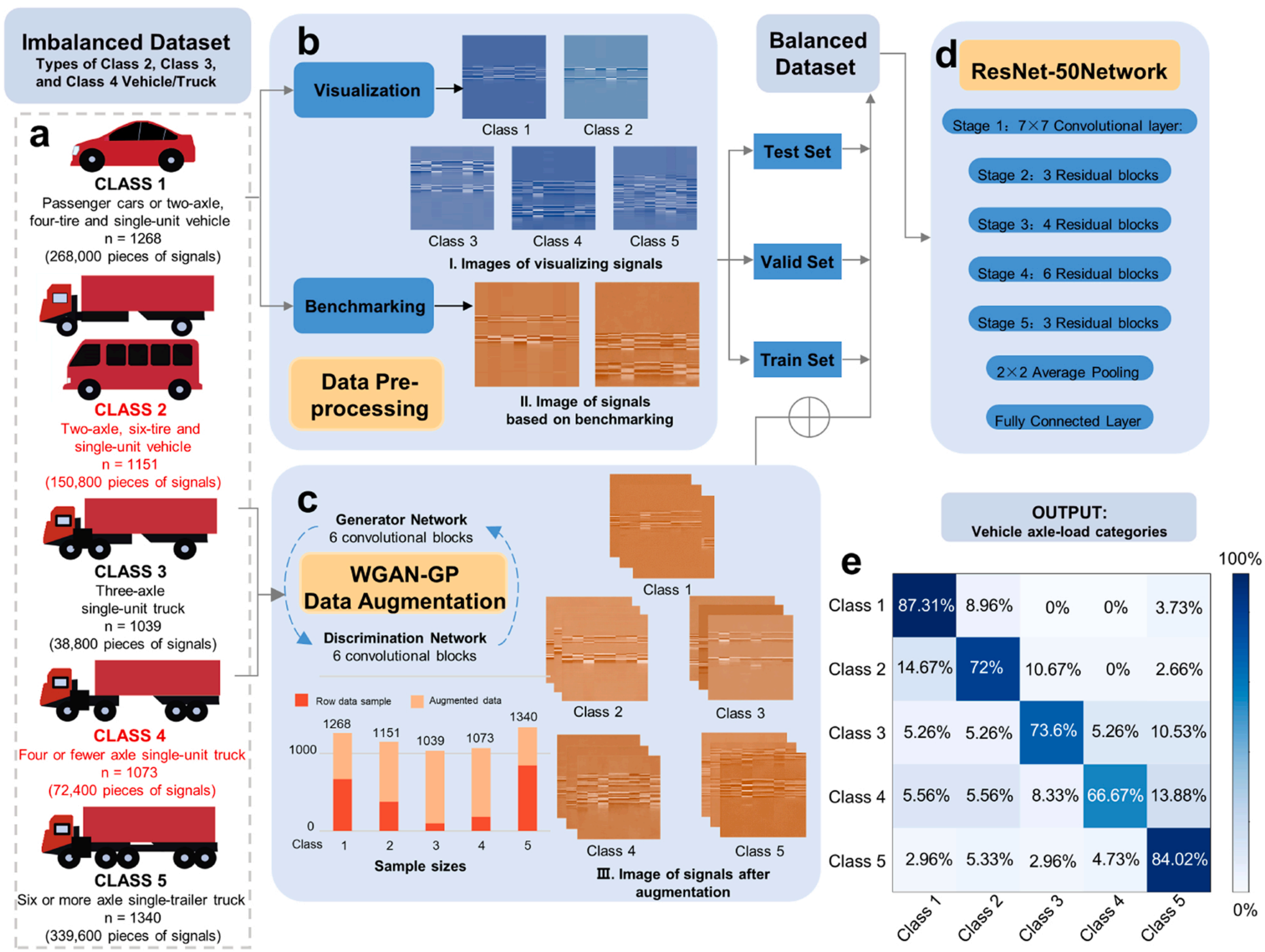

Fig. 3. Data Analysis. a. Imbalanced vehicle signals dataset after manual labelling (including 670 passenger cars or two-axle, four-tire and single-unit vehicles, 377 two-axle, six-tire and single-unit vehicles, 97 three-axle single-unit trucks, 181 four or fewer axle single-trailer trucks and 849 six or more axle single-trailer trucks). b. Signals pre-processing - Visualization & Benchmarking. c. A balanced vehicle signals dataset augmented by the WGAN-GP model (including 1268 passenger cars or two-axle, four-tire and single-unit vehicles, 1151 two-axle, six-tire and single-unit vehicles, 1039 three-axle single-unit trucks, 1073 four or fewer axle single-trailer trucks and 1340 six or more axle single-trailer trucks). d. ResNet-50 deep learning algorithm were used for analyzing axle load types of different vehicles. The composition of training, validation and test set (including 5000 training images, 438 validation images and 433 test images). e. Confusion matrix of each type of vehicle axle load of ResNet-50 residual neural network.

Table 2
Axle load type classification and dataset for deep learning algorithms for real traffic signals data. After manual calibration, a total of 6 types constituted the dataset of vehicle axle load in this study. Specifically: according to FHWA TMG, Type 2 was passenger car; Type 3 was two-axle and four-tire, single-unit vehicles; Type 5 was two-axle, six-tire and single-unit vehicles; Type 6 was three-axle single-unit trucks; Type 8 was four or fewer axle single-trailer trucks; Type 10 was six or more axle single-trailer trucks. Then, Type 2 and 3 was merged into the same class (Class 1). Thus, the vehicle axle load was classified into 5 categories finally, which were passenger cars or two-axle, four-tire and single-unit vehicles (Class 1), two-axle, six-tire and single-unit vehicles (Class 2), three-axle single-unit trucks (Class 3), four or fewer axle single-trailer trucks (Class 4) and six or more axle single-trailer trucks (Class 5).

Vehicle types	Type 2 Class1	Type 3	Type 5 Class2	Type 6 Class3	Type 8 Class4	Type 10 Class5	SUM
Dataset before augmentation using WGAN-GP							
Pieces of signals (pieces)	268,000		150,800	38,800	72,400	339,600	**869,600**
Train set (unit)	402		226	58	108	509	**1303**
Validation set (unit)	134		76	20	37	171	**438**
Test set (unit)	134		75	19	36	169	**433**
SUM (unit)	**670**		**377**	**97**	**181**	**849**	**2174**
Dataset after augmentation using WGAN-GP							
Train set (unit)	1000		1000	1000	1000	1000	**5000**
Validation set (unit)	134		76	20	37	171	**438**
Test set (unit)	134		75	19	36	169	**433**
SUM (unit)	**1268**		**1151**	**1039**	**1073**	**1340**	**5871**

Table 3
Architecture of WGAN-GP used in this study. Detailed network structure of WGAN-GP Generative and Discriminant network.

Generator			Discriminator		
layer	K, S, P	Output shape	layer	K, S, P	Output shape
Input z	—	100 × 1 × 1	Input	—	32 × 224 × 224
1	4, 1, 0	256 × 4 × 4	1	8, 2, 1	32 × 110 × 110
2	8, 2, 1	128 × 12 × 12	2	8, 3, 0	64 × 35 × 35
3	4, 3, 1	64 × 35 × 35	3	4, 3, 1	128 × 12 × 12
4	8, 3, 0	32 × 110 × 110	4	8, 2, 1	256 × 4 × 4
5	8, 2, 1	32 × 224 × 224	5	4, 1, 0	1 × 1 × 1

terms of the type of vehicle axle load signals images that have been correctly classified as well as the misclassification cases for each class. As can be seen from the confusion matrix in Fig. 3e, the network has a strong discriminatory ability to distinguish passenger cars or two-axle, four-tire and single-unit vehicles and six or more axle single-trailer trucks, reaching 87.31% and 84.02% respectively. The values on the diagonal of the confusion matrix represent the number of samples correctly identified for each category.

ROC and AUC [43] are also criteria to measure the performance of the classifier. Generally, when the ROC curve is closer to point (0, 1), that means the classifier is close to perfect. The ROC curves of each vehicle axle-load type are plotted severally in Fig. 4e. The area under the ROC curve is the AUC value, which reveals the distinction of the model between positive and negative samples, is expected to be closer to 1. In this study, the model scored an AUC of 0.95, which demonstrated an outstanding performance in predicting the types of vehicle axle load. The AUC values of passenger cars or two-axle, four-tire and single-unit vehicles, two-axle, six-tire and single-unit vehicles, three-axle single--unit trucks, four or fewer axle single-trailer trucks and six or more axle single-trailer trucks are 0.95, 0.93, 0.94, 0.92 and 0.95 respectively (Fig. 4e).

4. Cloud platform, mobile terminal testing and outlook

Based on the desktop-level deep learning, we also developed a mobile traffic signal information monitoring system based on cloud platform and Android framework, which enabled engineers to obtain the vehicle axle-load information mobilely (Fig. 4a). The trained deep learning model was transferred to TFLite mobile model and then inserted into Android project with the Android Studio software. In addition, Activity, Layout, UI interface and Service ect. were also designed with the help of the Android Studio development software using Android-JAVA language. Finally, a software package (APK file) called “Smart Road” monitoring application can be automatically generated after virtual compiling and debugging.

Our system can be deployed on common mobile terminal devices, such as mobile smartphones, autonomous car navigators and so on. The information transmission between mobile devices and cloud platform was achieved by Message Queuing Telemetry Transport (MQTT) connection using 5 G or 4G wireless technology (Fig. 4b). The devices acquired vehicle real-time signals from the cloud platform and analyzed the signals based on the mobile deep learning model. The final

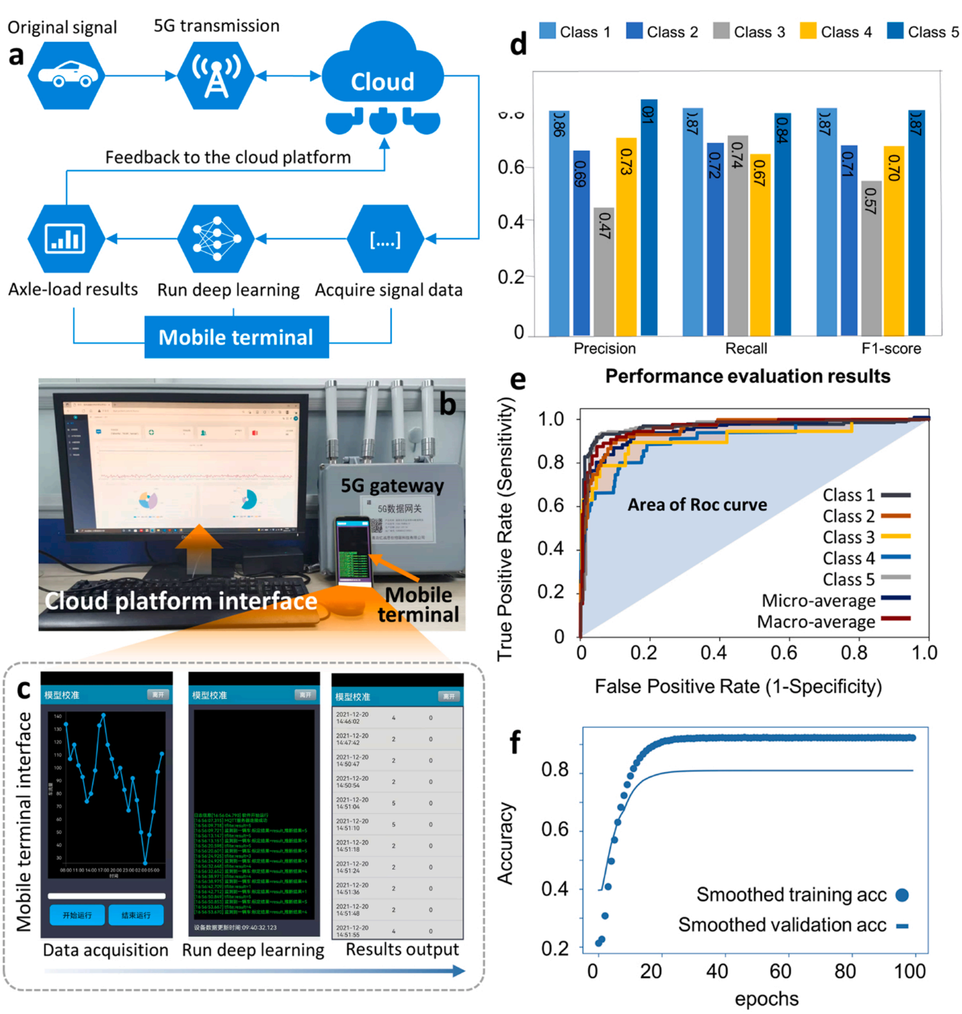

Fig. 4. The cloud platform and application deployment. a. The process of application development. The development process included converting TFLite, building Android project in Android Studio platform, generating APK package and installing mobile application. b. The homepage of the cloud platform. top column. system information, the number of terminal devices, APP users and operating results. middle. the presentation of CPU usage and memory usage. bottom pie chart. the number of vehicles in different axle-load and the accounting ratio of vehicles in each axle-load type. c. Presentation of the application. In the APP, the classification result of vehicle axle-load signals can be acquired in real time. d. Model results. Classification performance metrics, including precision, recall rate, F1-score value of each type of vehicle axle load. e. ROC and AUC demonstrated the classification model overall performance and the classification effect of each type of vehicle axle load. f. Accuracy curves of the train and validation set are also presented. The final test accuracy of the model reached 81.06%.

classification result of vehicle axle-load can be displayed in the application and fed back to the cloud platform for saving and analysis. Fig. 4c presents the analysis process of traffic axle-load information on the mobile terminal. The proposed system is closer to practical engineering utilization, which can not only be applied in smart monitoring and management of transportation information and infrastructure etc., but also offer a low cost and highly reliable decision-making system to road users.

Our proposed SSTISs can be widely applied in sensing, wireless transmission and analysis of signal data of transportation infrastructure in the future smart cities, as shown in Fig. 5. Vehicle signals collected by the TENG sensors can be transmitted by advanced wireless communication technology to the brain of smart cities (the cloud platform). With its vast storage and computing power, the platform processed and analyzed the traffic information efficiently. The platform in this study mainly includes the deployment of back-end server and front-end website (Fig. 5a). The databases named MongoDB and MySQL were built by Python programming tool acted as the transmission intermediary of the TENG sensors between the communication gateway and terminal equipment. The presentation front-end was developed using the VUE framework. Users' information, the running results of artificial intelligence-based models, CPU usage and memory usage can be present on the homepage of the platform. In addition, the platform enabled to realize the operational management of terminal devices, deep learning models and real-time vehicle monitoring information.

5. Conclusions

This study is an innovative design and engineering application of the self-powered flexible sensors for smart transportation monitoring, which provides a significantly innovative approach for advanced sensing in smart cities. The authors systematically proposed a new smart clean-energy based transportation infrastructure skin (SSTIS) system integrating the bionic TENG sensors and the deep learning models, which can perceive, acquire, and analyze the real-time vehicle type information. The feasibility of the self-powered TENG sensor was tested by the full-scale Accelerated Pavement Test and field test, verifying that the sensors can accommodate different transportation situations and severe natural environmental conditions. ResNet-50 network was used to capture and identify different axle load characteristics of the vehicles and achieved a precise performance with an accuracy of 81.06% and a micro-averaged AUC & ROC of 0.95. On this basis, the authors developed a mobile vehicle axle-load monitoring system. The application is designed for any embedded systems such as Android devices.

With SSTIS system proposed in this study, a self-powered, intelligent, and accurate monitoring of civil infrastructures such as vehicles, roads, bridges, and buildings can be achieved, to realize the regular functions in a smart city. Besides, with the fast development of commercial 5th generation wireless (5 G) technologies, the transmission between things and the cloud platform (i.e. city brain) will become faster and more stable. And with the help of the strong computation ability of the cloud platform, the whole city can operate and run more intelligently. Furthermore, the mobile intelligent monitoring and analysis has been preliminarily developed by the authors using TensorFlow Lite by Google. The developed Android application named "Smart Road" in this study can be deployed on smart phones, autonomous cars and so on for all the mobile computation scenes. It used an Android application and wireless communication technology to achieve fast, reliable communication between traffic infrastructure and road users. In general, SSTIS provides a powerful tool in achieving a self-powered real-time and sustainable monitoring in the smart city of the future.

CRediT authorship contribution statement

Qiang Zheng: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition, Supervision. **Yue Hou:** Conceptualization, Software, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Resources, Project administration, Funding acquisition. **Hailu Yang:** Methodology, Investigation, Writing – original draft. **Puchuan Tan:** Methodology, Investigation, Formal analysis, Writing – original draft. **Hongyu Shi:** Software, Investigation, Formal analysis, Writing – original draft. **Zijin Xu:** Investigation, Data curation. **Zhoujing Ye:** Investigation, Writing –

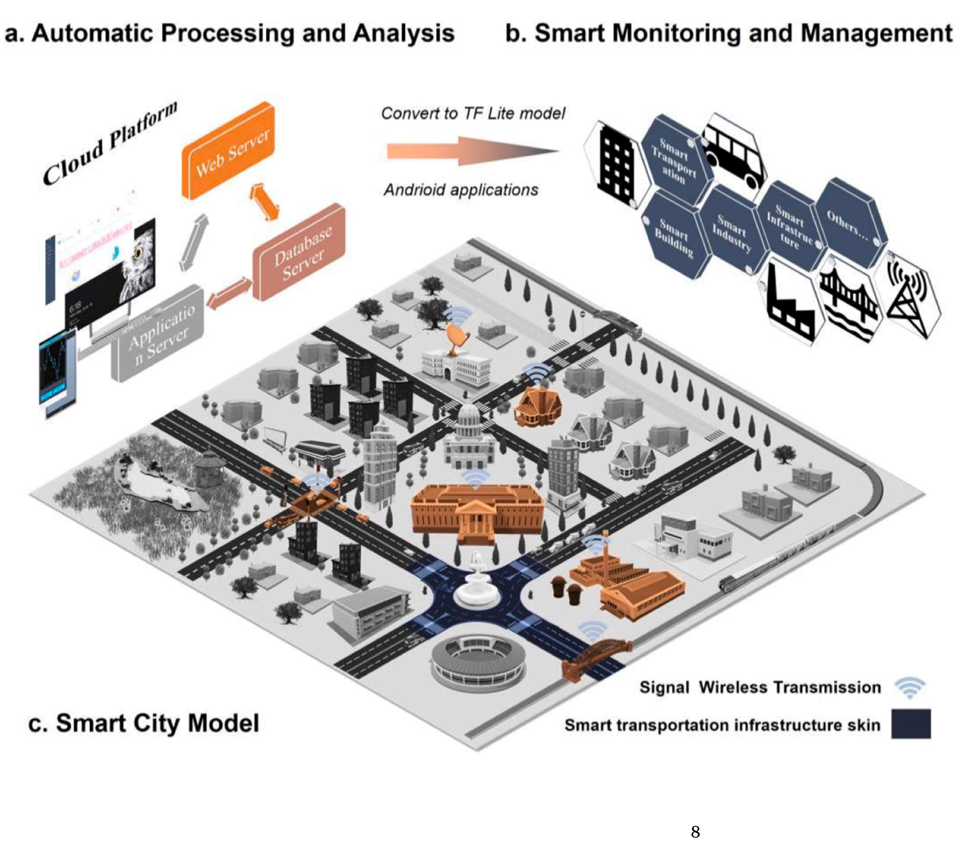

Fig. 5. Sensing, transmission and analysis based on signal wireless transmission, cloud platform and artificial intelligence in smart cities using SSTIS. a. Monitoring signal data of urban infrastructure was transmitted to the cloud platform. With its powerful computing and storage capabilities, the whole city will be monitored continuously and become more intelligent. b. An application, which can be deployed on mobile phones can be widely applied in smart transportation, smart industry and other fields. c. SSTISs were pasted on the surface of vehicles, roads, bridges and buildings etc. in the smart city to exchange different crucial information.

original draft. **Ning Chen:** Software, Formal analysis. **Xuecheng Qu:** Investigation. **Xi Han:** Investigation. **Yang Zou:** Investigation. **Xi Cui:** Investigation. **Hui Yao:** Formal analysis. **Yihan Cheng:** Investigation. **Wenhan Yao:** Investigation. **Jinxi Zhang:** Investigation. **Yanyan Chen:** Investigation, Writing – original draft. **Jia Liang** : Investigation. **Xingyu Gu** : Investigation. **Dawei Wang** : Investigation. **Ya Wei** : Investigation. **Jiangtao Xu** : Investigation. **Baohong Jing:** Software. **Zhu Zeng:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Project administration, Supervision. **Linbing Wang:** Conceptualization, Software, Formal analysis, Writing – original draft, Writing – review & editing, Resources, Project administration, Supervision. **Zhou Li:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Project administration, Supervision, Funding acquisition. **Zhong Lin Wang:** Writing – original draft, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The datasets generated during and/or analysis during the current study are available from the corresponding author upon reasonable request. The source code used in this study is available from the corresponding author upon reasonable request.

Acknowledgments

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CRediT authorship contribution statement

Qiang Zheng, Puchuan Tan, Xuecheng Qu, Yang Zou, Xi Cui, and Zhou Li designed the TENG sensor. Yue Hou, Qiang Zheng, Hailu Yang, Puchuan Tan, Zhoujing Ye, Wenhan Yao, Linbing Wang, and Zhou Li completed the in-door fatigue test of the TENG sensor. Yue Hou, Hailu Yang, Puchuan Tan, Hongyu Shi, Zhoujing Ye, Yihan Chen, Ya Wei, Linbing Wang, and Zhou Li participated in the full-scale accelerated pavement tests (APT). Yue Hou, Ning Chen and Hongyu Shi processed the experimental data and develop the deep learning LSTM model. Qiang Zheng, Yue Hou, Hailu Yang, Puchuan Tan, Hongyu Shi, Zijin Xu, Zhoujing Ye, Yihan Chen, Jia Liang, Xingyu Gu, Linbing Wang, and Zhou Li designed the field test and collected the real traffic signals data in Nanjing City, China. Yue Hou, Hongyu Shi, Ning Chen, Jiangtao Xue and Zhoujing Ye preprocessed signals data. Yue Hou, Hongyu Shi, and Ning Chen developed, trained the deep learning algorithms and performed the final evaluation of model performance. Yue Hou, Hongyu Shi, and Baohong Jing developed the cloud platform and mobile terminal deep learning application. Qiang Zheng, Yue Hou, Hailu Yang, Puchuan Tan, Hongyu Shi, Zhoujing Ye, Hui Yao, Jinxi Zhang, Yanyan Chen, Zhu Zeng, Linbing Wang, Zhou Li and Zhong Lin Wang rote the manuscript with feedback from all authors.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.nanoen.2022.107245.

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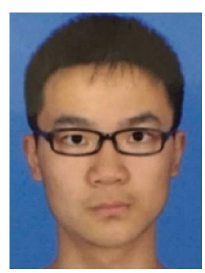

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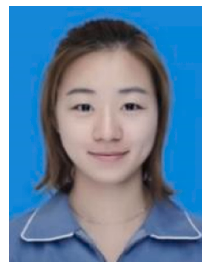

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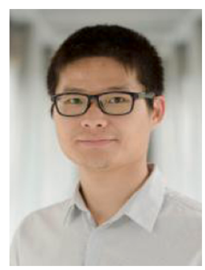

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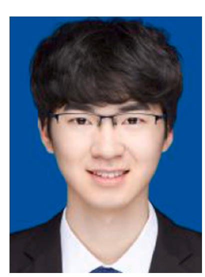

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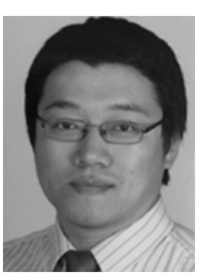

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