Deep Learning Based Pothole Detection and Reporting System

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Abstract*—Humps and potholes are the foremost reasons for road accidents. It should be detected and informed to the other vehicle that is going to pass in that location leads to reduce accidents. To overcome this problem, in this paper, a novel road surface monitoring system is proposed for identifying the humps and potholes. The signals scattered from the ultrasonic sensor influenced to a large extent by the hump, and potholes of the road. Due to a reduction in the amplitude of the reflected signal, the above problem is hard to analyze. For real-time analysis, Kirchoff's theory has used. To overcome the limitations of Kirchoff's theory, Convolutional Neural Network-based Deep Learning (CNN-DL) has proposed for detecting the pothole and humps on the road. The location of the pothole has measured by a global positioning system (GPS) and updates the information to the control room. To prove the validity of the proposed method for estimating the potholes on the road, two other benchmark methods, namely, Kirchoff's theory, and k-nearest neighbor (KNN) are selected to validate the performance. The experiment results show that the CNN-DL is better than other methods for detecting pothole of the road at any kind.

***Keywords*—road surface monitoring, deep learning, convolutional neural network, k-nearest neighbor, global positioning system**

I. INTRODUCTION

The infrastructure developments of a country define its economic growth and success. Development of infrastructure meets several challenges, and a sound organized network is useful for industry, social mobility, business, and communication of a nation. The highway infrastructure should be maintained, and the damages may be the reason for the growing amount of accidents. Highway transport is a significant mode of transportation in India. Road irregularities cause leads to damage the vehicles. A Gaussian model algorithm has used to detect the abnormal event, and the severity estimation algorithm has used for finding the relation between vertical acceleration and vertical displacement [1]. Ground-penetrating radar was used to detect the crack in different width of the road. An experimental setup was used for detecting the cracks in the road. The result showed the possibility of crack detection that depends on the layers of cracks [2].

A model has been developed, comprising the problems, used data, and a method. It has developed using the Negative binomial using the Negative binomial probability distribution, and to evaluate the model, a stepwise approach has used to assist the fitness of the model. The likelihood ratio test was used to derive the result of a crash prediction model [3]. An efficient non-parametric method was used to estimate the surface of the highway. To detect the planner and non-planner road surface benchmark and performed an extensive evaluation. The result showed that better accuracy of the detection under running conditions [4]. An autonomous data acquisition for the highway has proposed by Yulu et al. [5]. A vision-based depth-sensing system has used to measure the problems of the road. A multi-sensor system has utilized for powerful data-fusion. Measurements carried out for the vehicle moving under normal speed conditions. The system is used for crowdsourcing for recurrent data collection from the road surfaces. High-resolution satellite images have used to estimate the location of damage, and post-earthquake pictures of the road have studied in [6].

Chellaswamy et al. suggested an internet of things based on pothole and humps detection system. It automatically updates the status of the highway in the cloud to reduce the accident. A road containing pothole has monitored by scattering signals of an ultrasonic sensor. The system updates the status of the road to the cloud and shares it to all the vehicles which are going to pass in that location for avoiding accidents. Hardware was developed and tested in Arduino Uno with ESP 8266 [7]. A novel detection method has used to detect the damage of the roads using SAR images. Line structure has used for roads in SAR, and they have extracted by Duda detector, and the damages have detected by removing line structure. Edgeworth and Kullback-Leibler divergence approach had used to detect the road damages. This process has done using Radar SAT-II [8]. Pothole detection not only avoids accidents and also eliminate damage the vehicles. The pothole present on the highway is as shown in Fig. 1. Alert information is sent to the driver about pothole and humps so that they can reduce the speed. The potholes on the highway are detected by using an ultrasonic sensor and measure its height and depth. The corresponding location can be detected by the GPS receiver. All the sensed information has been updated in the cloud. An application program was

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developed to get a visual and sound alert [9]. The load assumption for the exhausting design of structures has studied by Kohler et al. 10]. Tugcu and Arslan implemented a novel approach using ANN for increasing the absorption rate of geothermal energy sources [11]. An organic Rankine cycle has used to study the performance of a back-propagation neural network with a support vector machine has suggested by Dong et al. [12]. Thermodynamic analysis has been carried out by Rashidi et al. for a refrigeration system. By using an engineering equation solver, the network was trained based on the thermodynamic model [13]. A deep learning method (DLM) and its efficiency have studied by Sze et al. [14].

Fig. 1. Potholes present in the highway.

In this study, CNN-DL based learning method has introduced to detect the pothole and humps present on the highway. The experiment has carried out under normal operating conditions of the vehicle. CNN-DL has not intended to detect the humps and pothole; it also estimates the strategy of the road. The deep learning approach evaluated under different conditions and compared with various supervised machine learning techniques. The rest of the paper is structured as follows: Section II describes the sensing of the surface of the road and the proposed system. The new method called CNN-DL algorithm has explained in Section III. Section IV compares the results of CNN-DL with other recent algorithms that have used to solve the optimization problem. Finally, the conclusions have discussed in Section V.

II. Proposed System

A. Road Surface Sensing

The highways are severely affected due to overloaded vehicle and massive traffic. It will create humps and potholes on highways. The quality materials used in the construction and environmental condition (temperature changes) also play a key role. Several investigations related to road pavement say that potholes have created due to vulnerable asphalt at low temperatures and excess of asphalt content, sand particles, and surface density. The data acquisition system which is mounted on the test vehicle, and run at different routes for estimating the problems on the surface of the highway. It has three major tasks that are input parameter initialization, read input from the accelerometer, and analysis through learning. For the data acquisition exercise, we used ADXL 335 accelerometer and ultrasonic sensor as input devices. The accelerometer and ultrasonic sensor were mounted at the bottom of the Zonata car model 2009 and run at 25 km/hr. A similar approach has done, and the performance of the system has studied in [15] motivated us to perform this experiment. The vibration due to loose-fitting can be avoided by suitably placing the accelerometer at the desired angle. To identify the location of highway anomalies a Global Positioning System (GPS) is incorporated in CNN-DL. The microcontroller ATmega328 has used to program the automatic detection of the pothole and send the corresponding location to the control room. The controller initializes the GPS module (Ublox NEO-M8N) capture and records the latitude and longitude coordinates when an anomaly is detected. The data points for estimating the location of pothole have been taken based on Khosravi et al [16]. The roughness index and the corresponding acceleration have considered for illustrating the quality of the highway. The signal has obtained from the sensor over a particular duration. We have included the roughness characteristics and trained CNN-DL based on the obtained roughness value of the highway. A threshold level has set to find the roughness index and estimate the anomaly present in the road.

B. Rough Surface of Road

It is significant to characterize the statistical parameters of a set of ordinary surfaces. The experimental measurement shows that the rough surface variation is close to Gaussian distribution. The rough surface profile along the x-axis and the height variation has defined along the y-axis. The variation is perpendicular to the z-axis. The function can define for a surface is expressed as:

$$Y=h(x) \tag{1}$$

Where h represents the deviation of height from the plane y=0, the mean plane through the rough surface is $<h>=0$.
The surface of the road using Gaussian statistics is characterized by

$$(h)dh = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{h^2}{2\sigma^2}\right] dh \tag{2}$$

where p(h) represents the probability of the surface height starts from -h and +h for a given variation, σ. Instead of representing the rough surface using (2), the discrete spatial values can be used. The equivalent discrete value with probability density function for the road surface can be expressed at the point, yi:

$$P(y_i) = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{y_i^2}{2\sigma^2}\right] \tag{3}$$

where i represent incremental changes down the x-axis and the right side term is the correlation length and it can be expressed based on the correlation function is given by

$$C(R) = \frac{<h(r)h(r+R)>}{\sigma^2} \tag{4}$$

The correlation function, 1/e is called the correlation length, and the scattering behavior is directly related to the surface of the road.

C. Total Signal Amplitude

The surface of the highway plays the most significant role in estimating the damage. The output of the ultrasonic sensor depends on the roughness characteristics of the highway. If roughness is more the diffusion will be increased. The peak-to-peak value is the sum of both the diffused signal and the coherent signal. The different realization has considered obtaining the scattering the response and estimates the average of the amplitude. In this paper, the two sensors have arranged in such a way that the coherent and diffuse signals have no phase difference. By using Kirchhoff's theory, the entire field has considered a combination of diffused and coherent signals [17]. The numerical approach to estimate the

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surface realization can be expressed as:

$$\emptyset_{total}^{\sigma} = \langle \emptyset_{i,N}^{\sigma} \rangle \quad (5)$$

III. Deep Convolutional Learning Machine

In this section, the received signal has analyzed using deep convolution learning is proposed. CNN-DL combines the fast processing of the learning machine and the performance of feature abstraction of CNN. Fig. 2 shows the basic structure of the CNN-DL. The CNN-DL classifier consists of n input layers, p=[P_1, P_2,…, P_m],, M number of neurons in the hidden layer (HL), h(a)=[h_1(k), h_2(k),…,h_N(k)] and k output layers [18]. After proper training the output weights of the hidden layer is estimated as:

$$A\gamma = D \quad (6)$$

where A *and* γ represents the hidden layer output matrix and output weights respectively. D is the classifier output. Now the classifier of the proposed CNN-DL can be expresses as:

$$\gamma = A^{*}D \quad (7)$$

The weights γ=[γ_1, γ_2, …, γ_N] and the biases b=[b_1, b_2, …, b_N] are generated randomly. The HL can be expressed as [19]:

$$H = \begin{bmatrix} h(k_1) \\ \vdots \\ h(k_m) \end{bmatrix}$$

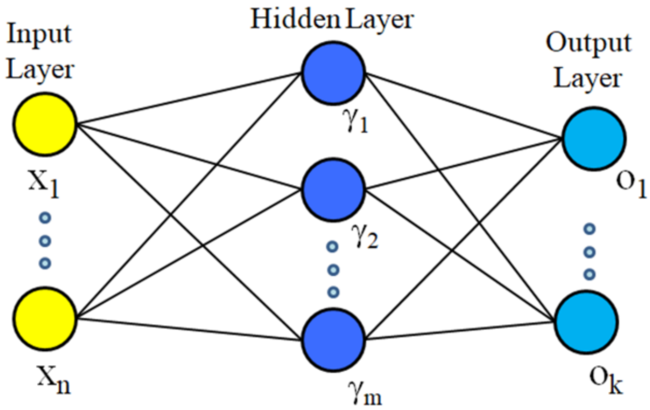


Fig. 2. Basic construction of deep learning machine.

$$= \begin{bmatrix} h_1(\gamma_1^T k_1 + b_1), \dots, h_N(\gamma_N^T k_1 + b_N) \\ \vdots \\ h_1(\gamma_1^T k_m + b_1), \dots, h_N(\gamma_N^T k_m + b_N) \end{bmatrix} \quad (8)$$

The inverse of the matrix H using Moore Penrose method can be written based on [20] as:

$$\gamma^{*} = H^{+}\gamma = \left(H^T H + \frac{1}{C}\right) H^T \gamma \quad (9)$$

where β^{*} is the unique solution and smaller norms provide lesser training error. The flow chart of the CNN-DL is shown in Fig. 3.

CNN-DL based pothole detection has six important steps.

1) The sensor inputs, namely, the accelerometer, and ultrasonic sensors and the targets are loaded.
2) The normalization process has carried out in this step.
3) The test data set and the training data sets are determined.
4) The network is built in the Matlab using the function 'newff' and 'tansig' is used for the hidden and output layer of the transfer function.
5) Performance comparison is done using statistical indicators.
6) Plotting the results.

A. Performance Evaluation Measures

Statistical indicators have used to evaluate the performance of the system. The pothole estimation in the highway using the proposed CNN-DL method utilizes different statistical indicators to assess the performance. The correlation coefficient (CC) and the root mean square error (RMSE) have used in this study. In RMSE, the low value indicates high performance of the pothole detection [21].

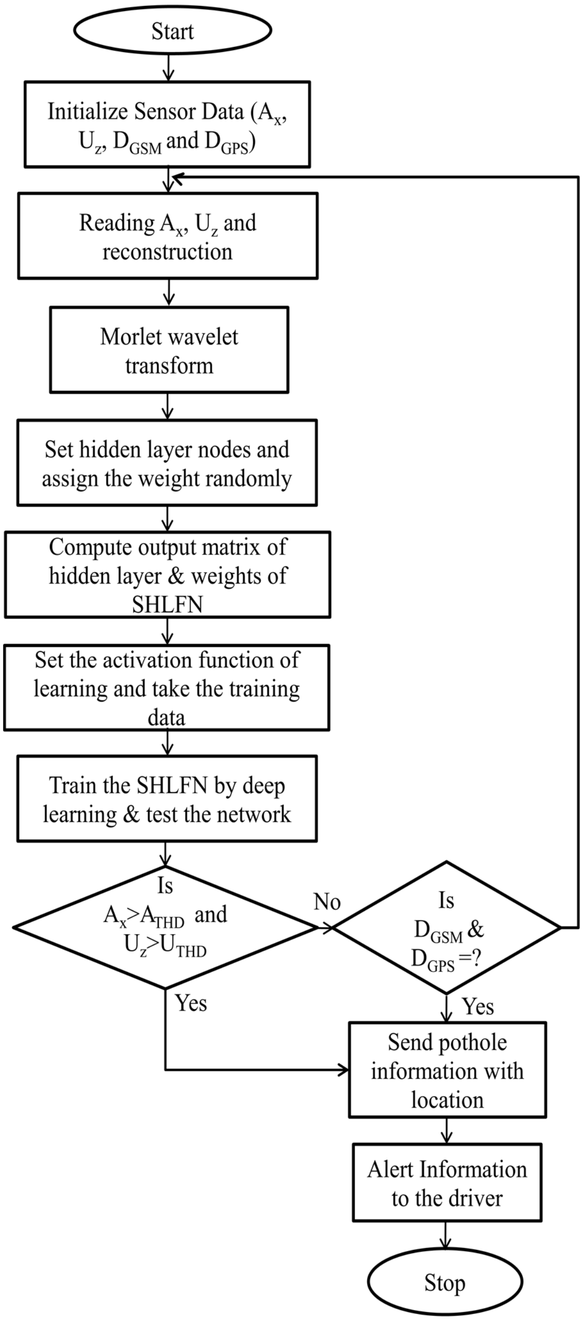


Fig. 3. Flow chart of the proposed CNN-DL method.

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(x_i - k_i)^2} \quad (10)$$

The relationship between the targets to the output is known as

CC. It can express as:

$$CC = \frac{\sum_{i=1}^{m}(x_i-\hat{x})(k_i-\hat{k})}{\sqrt{\sum_{j=1}^{m}(x_i-\hat{x})^2 \sum_{j=1}^{m}(k_i-\hat{k})^2}} \tag{11}$$

Where m is the number of data, x_i and k_i represents the observed value and estimated value respectively. $\hat{x}$ is the mean of observed data, and $\hat{k}$ is the mean of predicted data.

IV. Result And Discussion

The signal has received from the sensors mounted in a vehicle for detecting the pothole and humps on the roads. Initially, the output of the ultrasonic sensor and accelerometer has measured, and the simulation has carried out using MATLAB 2018. The maximum roughness is taken s=0.4 Υ_{in} in this study. The signals have measured for different roughness, and the output has plotted. When the degrees of unevenness increases the convergent solution decreases. The convergence characteristics of the proposed CNN-DL have compared with the two other methods, namely, Kirchhoff theory and KNN method.

TABLE I. Accuracy of Prediction of Pothole for Different Methods.

Methods	RMSE		CC	
	Training	Testing	Training	Testing
CNN-DL	3.220e-03	3.173e-03	0.9537	0.9638
Kirchhoff Theory	5.846e-02	5.638e-02	0.8928	0.8973
KNN method	4.958e-03	4.773e-03	0.8184	0.8274

To study the performance of CNN-DL, three different routes on the highway had considered and tested. Three different roughness such as s=0.115μ_{in}, s=0.200μ_{in}, and s=0.325μ_{in} has selected, and the corresponding variation in the received signal was measured and shown in Fig. 4. It is observed that when the surface variation increased the amplitude variation also increased. Several iterations are required to reduce the variation present in the amplitude. In case, if the roughness has increased, the number of realization should be increased, it leads to an increase in computational time.

TABLE II. Pothole Detection at Different Locations and the Corresponding GPS Coordinates

Methods	Vehicle Speed	Pothole Location	Latitude	Longitude
CNN-DL	30 km	Adyar	13.0013° N	80.2565° E
Kirchhoff Theory	30 km		13.0014° N	80.2566° E
KNN method	30 km		13. 0014° N	80.2565° E
CNN-DL	50 km	Saidapet	13.0213° N	80.2231° E
Kirchhoff Theory	50 km		13.0215° N	80.2232° E
KNN method	50 km		13.0213° N	80.2232° E

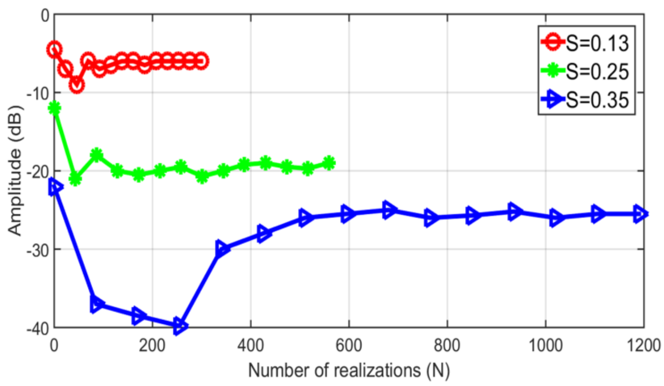


Fig. 4. Amplitude variations of reflecting signal for three different roughness.

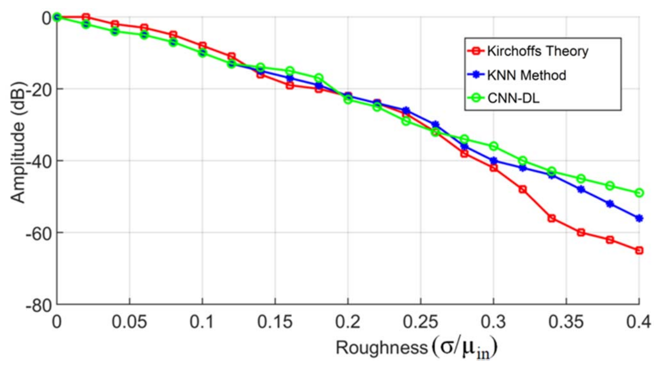
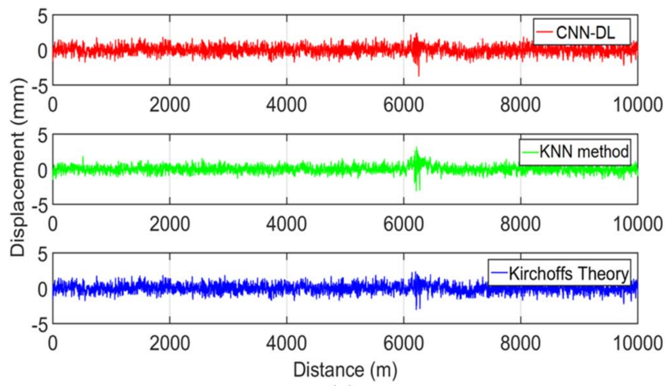
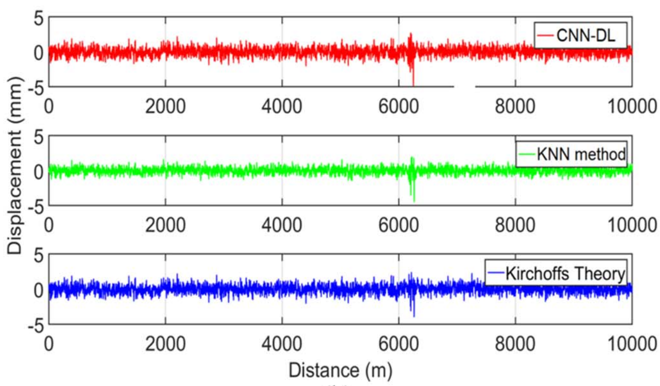


Fig. 5. Experimental result of CNN-DL and two other methods under different roughness.

The roughness surface and the corresponding amplitude of the reflecting wave using the proposed method, Kirchhoff theory, and KNN method have shown in Fig. 5. Fig. 5 indicates that when roughness has increased, the amplitude of the reflecting wave gets decreased. The comparison results show that the



(a)



(b)

Fig. 6. Signal received from the accelerometer (a) 30 km (b) 50 km.

proposed method provides better results than the Kirchhoff theory and KNN methods. If the pothole is detected, the corresponding GPS coordinates (latitude and longitude) have captured by the controller. The pothole has identified through the vibration signal that has received from the accelerometer.

The MEMS accelerometer has mounted on a horizontal plate in the bottom portion of the vehicle. The pothole has identified in a specific location, and the test has conducted under two different speed scenarios (30 km and 50 km). The measured acceleration using the proposed and two other methods for the two-speed scenarios have illustrated in Fig. 6 (a) and (b) respectively. Comparing the performance of CNN-DL with the other two benchmark methods, the CNN-DL is better than KNN and Kirchhoff theory methods.

The performance comparison in the prediction of the proposed CNN-DL and two other methods for pothole detection has presented in Table 1. Different parameters have considered: a number of iterations: 200; the size of the swarm: 200; the number of fuzzy rules: 8; social coefficient: 4-C1; and cognition coefficient: 2. Using the parameters experiment was conducted and observed the result. The result indicates that the pothole with location information is exactly identified by CNN-DL than KNN and Kirchhoff theory methods. It is observed from Table 1 that the proposed CNN-DL provides less RMSE, 3.220e-03 in training and 3.173e-03 in testing and greater CC in 0.9537 in training and 0.9638 in testing in pothole detection.

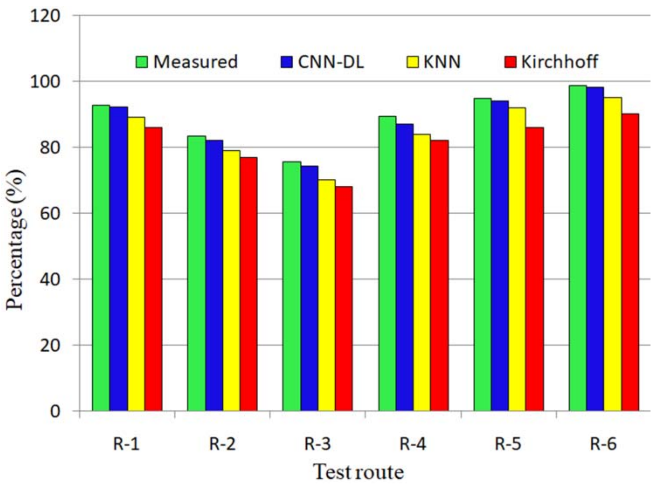


Fig. 7. Results of the pothole classification

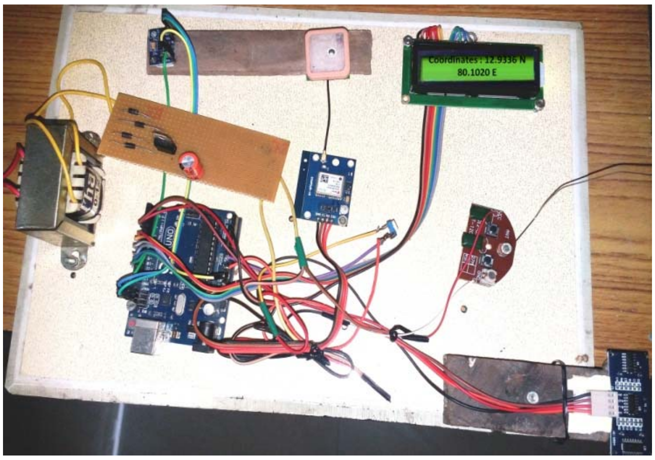


Fig. 8. Experimental setup of CNN-DL.

To validate the proposed method six different locations have been chosen. The estimation result is not accurate when using a single classification method for total measurement. Hence, the measured highway profile is segmented based on the distance. Fig. 7 shows the validation results of the six test route for the proposed CNN-DL and two other benchmark methods. The six highway profile consists of class A road, class B road, and a combination of both. The result shows that the measured highway profile and the classification using the proposed CNN-DL provide better than the other two methods. From the entire test route, the measured highway profile and the classification using the proposed method are almost equal. The classification result of 99.2% was achieved by CNN-DL, 95.4% was achieved by KNN, and 89.3% was attained by the Kirchhoff method.

Fig. 9. Experimental result for detection of pothole.

The experiment was carried out for two different locations at two different speeds in the Chennai area is listed in Table 2. The GPS coordinates of the corresponding pothole location are also measured by the system using the proposed method and the other two methods. From Table 2 one can easily understand that in both the speed scenarios the proposed CNN-DL exactly detecting the location of pothole followed by the KNN method and Kirchhoff Theory method.

Fig. 8 shows the experiental set up of the proposed system interfaced with GPS, accelerometer, and ultrasonic sensor. The accelerometer and the ultrasonic sensor have placed on a flat surface of the vehicle. If any pothole has detected the information sent immediately to the control room. The GSM has interfaced with the controller, and the controller captured the coordinates when a pothole is detected. It sends the information to the mobile number that has stored in the program. The LCD of Fig. 9 shows a pothole detected at the coordinates N=13.0013; E=80.2565. It has observed from the GPS coordinates the CNN-DL accurately identifies the pothole in an exact location.

V. CONCLUSION

The highway pothole detection and information system are proposed based on the CNN-DL algorithm. Two different sensors (accelerometer and ultrasonic sensor) have placed in a vehicle for comparing the signal, and the algorithm takes the decision of the pothole and picks the corresponding location if the pothole has identified. The effect of surface variation has studied under two different speed variations, and the simulation has done using MATLAB 2018. CNN-DL has compared with two state-of-art methods, namely, Kirchhoff theory, and KNN method for comparing its performance. The results show that the CNN-DL performs better than the two other benchmark methods. To evaluate the proposed CNN-DL two statistical methods have used. The result shows that the proposed CNN-DL efficiently detects the pothole at all levels. The experimental setup has

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constructed, and the different tests have conducted. The test result indicates that the proposed method accurately identifies the hump and pothole with location information. The pothole information of highways will be shared with the control room with an alert for necessary action.

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