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Classification of Road Cracks using Deep Neural Networks

Meghana A
Computer Science and Engineering
Velagapudi Ramakrishna Siddhartha Engineering College
Kanuru, Vijayawada
meghanaa539@gmail.com

Sridhar K T V S
Computer Science and Engineering
Velagapudi Ramakrishna Siddhartha Engineering College
Kanuru, Vijayawada
tanujkaruturi@gmail.com

Manasa M
Computer Science and Engineering
Velagapudi Ramakrishna Siddhartha Engineering College
Kanuru, Vijayawada
masanammanasa123@gmail.com

Sai Greeshmanth Ch
Computer Science and Engineering
Velagapudi Ramakrishna Siddhartha Engineering College
Kanuru, Vijayawada
greeshhard@gmail.com

Rajeswari S
Computer Science and Engineering
Velagapudi Ramakrishna Siddhartha Engineering College
Kanuru, Vijayawada
rajeswari.setti@gmail.com

Abstract— **Roads play an important role in the economic development of a country. Along with economic development, they even provide social benefits such as traveling with ease and reduce the accidents caused due to poor road maintenance. With the above-said importance of the road, a means of transport, poorly maintained roads may reduce mobility and even lead to a significant increase in road accidents and vehicle operating cost. These cons of poor road maintenance emphasize the need for frequent and quick road damage detection. Road damage detection is an important part of road maintenance, which requires a huge manual effort to get the task done. This work can be done within a minimum time by developing a model that will be able to detect the type of cracks present in the image. In this project, the user is provided with an option to upload the damaged road image which is analyzed against the yolov3 model which can detect whether the road crack is among pothole, alligator crack, longitudinal crack, and lateral crack. This result will be stored in an excel sheet along with the location details of the road crack. Next to this, this research study defines the condition of the road by using the same image as an input to a CNN model. In this way, a supervised deep neural network has been trained to detect road damage and save the data attained.**

Index terms: **Road Damage, Deep Neural Networks, Yolov3, CNN.**

I. INTRODUCTION

Frequent road maintenance is important for safe driving and is one among the major decrees of transportation and corresponding maintenance authorities. The principal factor for maintaining a safe driving environment is to efficiently monitor road damage which may take manual effort and time. It henceforth, becomes extremely difficult to monitor road cracks manually, and thus, the demand to successfully implement machine learning and computer vision algorithms gains a notable importance. This project aims to detect the road damage by using deep neural networks, which would help in the road monitoring activity without the need for any human intervention in examining the road cracks. The overall procedure of manual inspection of the surface is expensive and extremely time-consuming. Therefore, to ensure constancy, a powerful system to automatically predict road cracks is proposed in this paper. Considering the advantages in recent times on using deep learning for computer vision problems, this research work implements a model trained on YOLO v3 object detection algorithm and a CNN model that can detect if the type of crack is among pothole, alligator crack, longitudinal crack, or lateral crack and define if the road condition is among good, poor, very poor, satisfactory respectively.

II. RELATED WORK

In Road Damage Detection using Mask R-CNN [1] the authors discuss the design and solution to road damage detection and classification. Automatic detection of damage and classification of damage in different weather conditions can be used to improve maintenance and autonomous driving. As mask-RCNN algorithm is used for object detection and instance segmentation of natural images, which perform a task in a fast manner and produce effective results. The drawback of this method is NVIDIA GeForce 1080Ti graphic card is used, which is not cost-efficient.

In Road Damage Detection using Transfer Learning for multiple countries [2] the aim is to design a road damage detection system that can be used in different countries. They mainly developed the system to meet three goals, for assessing the usability of the model developed in Japan for other countries, it also proposes to use large heterogeneous datasets that contain images collected from different countries using smartphones and they also propose models capable of identifying and classifying damage in different countries (more than one country). Says that training the model with a heterogeneous dataset that contains images from different countries will give better results. The model discussed in this paper cannot reach its aim to give a model which can be used globally.

In Detection of Road Crack using Adaptive Thresholding and Convolutional Neural Network [3] the main novelties include a kmean clustering-based image segmentation algorithm in which images are smoothened using bilateral filtering and a fully connected neural network for image classification. Usage of bilateral filtering reduces the noisy pixels maintaining the edges between cracks and road surface. This method is not suitable for real-time applications as it is computationally expensive and the size of the neighborhood should be large enough so that it can cover sufficient pixels from foreground and background, or else it may lead to a poor threshold.

In Using U-Net based CNN for Pavement Crack Segmentation [4] this method made use of one cycle learning schedule based on cyclical learning rates to speed up the convergence. Introduced the concurrent spatial and channel squeeze and excitation modules in the proposed network architecture to increase the performance and use of various techniques. The use of SCSE modules leads to better performance along with the use of various training techniques. U-Net vogue architectures might hamper within the deeper models' middle layers, which bags some risk of ignoring the layers wherever abstract options square measure drawn by network learning.

In using Unsupervised Disparity Map Segmentation for Road Damage detection [5] the aim of this paper to use the unsupervised disparity mapping segmentation technique to detect road damage. To train the model they made use of datasets KITTI, Apollo Scape, EISATS with each having a good number of images. This method shows the damaged area effectively using segmentation. The drawback of this method is a user need to be using the machine of particular requirements which may not be feasible every time.

In a comparative analysis made for pavement distress classification [6] using different deep learning frame works, the result of this states that YOLO algorithm performed better than the remaining algorithms like CenterNet and EffecientNet with an F1 score of 0.58 which is nearly 20% more efficient than the others. The analysis was done on the dataset containing images of damaged pavements from Japan, Czech Republic and India. Transfer learning is used for training all the models in order to use information from the previous jobs. The major drawbacks are requirements of high graphical specifications due to extensive use of transfer learning and the disability of the model to identify transverse cracks and the damaged area in images with more shadows.

From a recent study using deep ensemble learning [7] for road crack detection, YOLOv4 is used for detection of different types of road damage. As YOLO takes input images with resolutions which are multiples of 32, more focus was kept on resolutions 416 and 608.Better results are obtained by giving input in the mentioned resolution and the performance of the model decreased if the resolution gets higher than these. A F1 score of 0.63 was obtained by ensembling 30 models. Even a high performance is achieved the process of putting 30 models together is a hectic task and even to make a small change for new updates while will take a lot of time.

In the study for Detecting and classifying asphalt pavement raveling with use of 3D technology and machine learning automatically [8] they used 3D laser technology for the detection of ravelling in pavement and classification into different classes based on severity is done by using RMST(root mean square texture).they used algorithm called stone way to identify the length gap and height gap of the missing stones by using 25-line laser sensing technology. They used a truck to carry all the equipment and scanned the road regions and calculated the aggregate level of severity of pavement raveling using RMST. Their equipment required is so large in amount and expensive and also there are better machine learning algorithms like CNN, R-CNN,YOLO which are more efficient.

In an article about Detecting pavement distress using DNN with orthoframes obtained by mobile mapping system [9] ,a set of orthoframes are collected before the training of the model using an equipment developed by Reach-U Ltd which has 6 high resolution cameras, attached to car which can picture panoramic view of the road. The obtained orthoframes are further reduced in number by removing some them which contain poor lighting and poorly distinguishable defects. Even the precision and accuracy of the obtained model is nearly 0.9,the data used for training the model is very small and cannot perform well with different type of images. The model is developed as a binary classifier which only says if the road is damaged or not but do not give any information about the type of damage.

In research discussing about Detection system for road crack that provides fully automatic road distress assessment [10] a vehicle furnished with two line filter cameras, a laser light framework and securing HW-SW is utilized to capacity the advanced pictures that will be additionally prepared through picture handling strategies to distinguish road cracks in offline. Pre-processing is done to both upgrade the linear features that might compare with damage and smooth the surface of the asphalt to facilitate the location interaction. A histogram examination is performed with that impact, bringing about a low size picture. Non-crack detection is then applied to explicitly isolate spaces of the pictures with joints, fixed cracks and white paint, that typically produce false positives. A seed-based methodology is proposed to manage road crack recognition Firstly, a Multiple Directional Non-Minimum Suppression (MDNMS) joined with a balance check is utilized to acquire the seeds. Then, at that point, a base distance cost map is registered in Cartesian directions for every one of the seeds gathering the most minimal expense from the focal point of a square locale of a pre-characterized size to the remainder of the pixels, including backtracking data. Consequently, seeds can be effectively connected into ways that need to meet certain balance conditions. The entire identification measure includes the utilization of a few boundaries, and their right setting turns into a critical part to get ideal outcomes without manual intercession. A completely programmed approach is proposed through a straight SVM-based classifier outfit ready to recognize the 10 distinct kinds of asphalt that show up in the Spanish streets. The boundaries are then tuned relying upon the yield given by the classifier. From one viewpoint, with respect to non-cracks recognition, results show that the presentation of such module decreases the effect of false positives. Then again, the noticed presentation of the road crack detection system is essentially supported by adjusting the boundaries to the sort of asphalt.

In Overview for adaptive activation configuring functions for deep neural networks [13] a comparative study the authors studied about different layer networks in DNN their filters and datasets used for training and testing. They studied different activation functions like Sigmoid, tanh, ReLU, Leaky ReL U,Maxout and ELU for each neuron in neural networks. The model proposed is feed forward network for continuous function of approximations, in which the concentration of units on network's surface depends on the concentration of units within the units. The architecture which is based on deep CNN has rectified linear units, which will gain more accuracy. We select a training dataset with normal distribution which will depend on large gradient regions. The spectral method is performing here to get a high numerical solution. The layer optimization includes non-linear function that is used for effective conditions on modern datasets. Finally, both adaptive model and network architecture are integrated to study optimization concepts. After observing the results, we can observe that based on loss function, every sperate layer in the network is optimized. Due to this reason classification accuracy is higher and errors are less when compared to other techniques.

In Study for finding facts behind preprocessing on deep learning algorithms [14] author looked to different aspects for performing deep learning-based algorithm and also why preprocessing is necessary over various deep learning-based applications. Deep learning is mainly used for three different operations mostly, they are classification, prediction and estimation. Various classification deep learning algorithms are taken and their results with and without preprocessing are compared. Other than in LSVC-Sentiment detection all the algorithms showed better results when preprocessing is used. Which gives strength to statement that preprocessing reduces noise and helps algorithm to concentrate on required or important areas. It also shows that using preprocessing gives better outcome for data, image and signal classification algorithms. But this study is only based on classification algorithms, not on prediction and estimation algorithms

In all our above survey we noticed that the models being used are either not compatible in real life situations due to the algorithm they choose or in some case the requirements of the project to function as the system requirements are expensive. Other drawback of some these methods is their prediction time. In these kind of projects applications need to be quick in classifying and predicting the output.

With the above said drawbacks in the related work we gone through, we came to this solution of using yolov3 model in detecting the type of cracks as it detects the output quickly and it would even produce a better accuracy in comparison to the other methods used.

III. TECHNOLOGIES USED

1. *Yolov3:*

YOLOv3 (You Only Look Once) is a real-time object detection algorithm that can identify objects within the image or videos that are given as input. Yolo uses a convolution neural network for object detection, which considers input images as a structured array and will be able to detect the specific objects within them. The dataset we use for training the model is labeled according to the yolov3 algorithm i.e, includes images and their corresponding text file of label index and respective boundary points. This version of yolo is considered better than its previous versions as it increases the performance like multi-scale predictions. The below process flow gives information about the process flow opted within the yolov3 in general whenever an image or video is given as input.

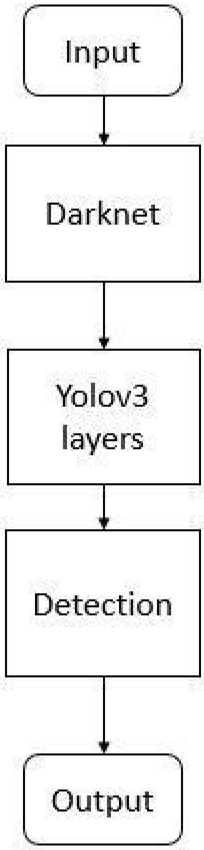

Fig. 1: General Process within yolov3

2. *Convolutional Neural Network:*

Convolutional Neural Networks were first introduced and used in the 1980s. Convolutional Neural Networks are also known as Convnets or by their acronym CNN. Initially, when CNN is developed, they are limited to the use like handwritten digit recognition used in banking for digit recognition on checks and in postal used for reading zip codes as CNNs need a large dataset. This case is again revisited in 2012 by Alexnet where large sets of data are available. Convolutional neural networks are a class of neural networks that consists of an input layer, output layer, and multiple hidden layers composed of artificial neurons that process the image given as input to the model. These artificial neurons are mathematical functions that calculate the weighted sum of multiple inputs and gives the activation value as output. Each neuron's behavior is defined by its weights. CNN is programmed using the Keras library in our paper. The process flow of a CNN model is given through below diagram.

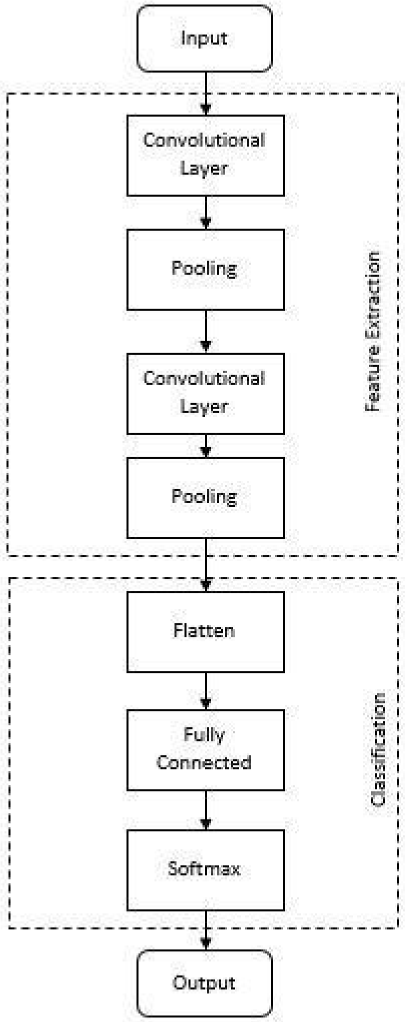

Fig. 2: Process Flow in CNN

3. Flask:

Flask is a python web application framework used in creating a web application. It is also termed to be a micro framework that is of little to no dependency on external libraries. This consists of two folders static and template in which the images to be displayed within the page are usually placed in the static folder and the Html files are placed in the template folder. Along with the flask technology, a python library flask-ngrok is made use in the project to demo or use our application present in our machine over the internet with the help of the ngrok tool.

4. Darknet-53:

Darknet is an open-source neural network framework in C, used with yolov3 for object detection. This consists of 53 layers as a series of convolution neural networks with 1x1, 3x3 dimensions. This is used as a feature extractor. We made use of darkent using its official pjreddie directory, cloning the required content in our project. The cfg file in darknet is altered according to the project requirements as the max batch size of 8000, having to classify among 4 classes.

IV. METHODOLOGY

Data Collection:

Yolov3 Model: Dataset from Kaggle is being used as the input to the model and this dataset consists of the images and the annotations of the images in text format that consists of the road crack type id i.e, for pothole-0,alligatorcrack-1, longitudinal crack-2 and lateral crack-3 followed by 4 values that are coordinates of the respective cracks present in the image used for classifying. This dataset consists of images of four types of crack as pothole, alligator crack, longitudinal crack and lateral crack which are of 1080p resolution and of 1920x1080 dimensions.

This dataset consists of 3321 image files and corresponding 3321 text files. These images are not confined to any specific crack it might be having one or more instance of the possible four types of cracks as specified and these corresponding text files will be having the data related to the image file it is referring to the image. Here the image and text files are binded as the same name is given to them.

CNN Model: Dataset from Kaggle is being used as the input to the model and this dataset consists of the four folders named as good, poor, satisfactory, very poor. These folders consist of the road damage images justifying the respective folder name. This dataset consists of nearly 2100 images.

Good folder consists of the images which road conditions are considered to be good, and this dataset consists of 845 files of these images. Poor folder are consisting of the images which road conditions are considered to be poor and this dataset consists of 396 files of these images. Satisfactory folder consisting the images which road conditions are considered to be satisfactory and this dataset consists of 515 files of these images.Very poor folder consisting the images which road conditions are considered to be not good and are very poor, this dataset consists of 318 files of these images.

Create a Yolov3 Model:

Yolov3 model is created using darknet53 framework. We start making our model by cloning the required darknet properties into our colab notebook. The model is trained for 8000 iterations against the dataset consisting road crack images of four types that is, pothole, alligator crack, lateral crack and longitudinal crack. Process followed in the yolov3 model working is as below,

1. Start the process by giving image as an input to the model.
2. When the image is uploaded the first step performed is Feature Extraction, in which the image will be made into nxn grid and results are obtained by the features embedded in different scales.
3. The output obtained in above step is sent to a detector a open source framework, darknet53 which consists of predefined weights.
4. Now the cracks in the images will be identified and the data is saved to a text file and based on the class names added we count the number of instance of particular crack.
5. Now these instance count is saved to the final excel sheet.

Create a CNN Model:

CNN model is created using python library keras and ReLU, softmax as activation functions. The model is trained against the dataset consisting of images saved in four folders defining the corresponding folder names, on which data augmentation is performed for better results. These images are not given as input to the model as it is instead they are initially resized into 224x224 image, converted to an array and this is given as input. Process followed in the CNN model working is as below,

1. Start the process by resizing the image into 224x224 and converting into an array.
2. Feature extraction is done by convolutional neural network using pooling technique
3. Now model will be able to classify the image into one among four possible classifications as poor, very poor, good, and satisfactory.
4. Road condition class obtained through above steps is given as output

V. PROPOSED SYSTEM

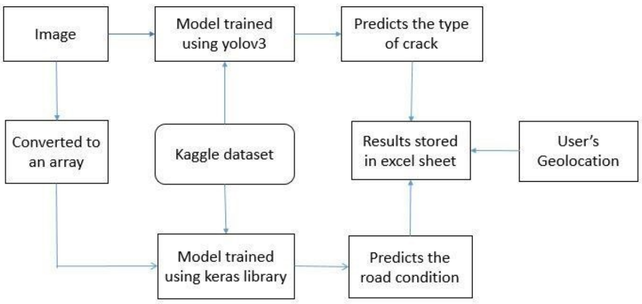

Fig. 3: Process Flow

The proposed system is a web application made using Html, CSS, javascript. As seen in Fig 1, the process starts when an image is uploaded that is when the image is given as an input to the model which is trained against a dataset of corresponding images. Yolov3 model trained so can identify whether a type of cracks within the image is among the pothole, alligator crack, longitudinal crack, lateral crack. This data obtained is saved in a text file internally within the ide and using python code we can get the count of the individual crack instances. Next to this, we will try to predict the road condition from the image. This is done through converting the given image to an array as the road condition detecting CNN model is built using the Keras library, which doesn't take an image as input instead consider images converted to an array. Now, this converted array is given as input to the CNN and it will be able to predict whether the road condition is one among the four possibilities, good, poor, satisfactory, very poor. The road condition feature is added to the fact that it helps in prioritizing the work better along with the individual crack count. Using the road condition data along with the crack count helps in delivering more promising and accurate results in taking any action.

This is the process followed on the image uploaded and the user is also asked to enter the location coordinates of the area where damage is noticed, and if the user is not aware ofthe coordinates they can use the website link provided to get the corresponding location coordinates and we can provide location coordinates using javascript geolocation function and they can store these details for later use. As of above when we obtain the location coordinates we will use the python geopy library to obtain the address in detail as postcode, district, state, and municipality. On completion of all the above-said process, we now save the data obtained into an excel sheet using the python library openpyxl. Here we'll save the data along with the date of upload, name of the image uploaded followed by the count of instances of the corresponding crack in the given image, latitude, longitude, district, municipality, state, postcode, and condition of road obtained through convolutional neural network model.

The process above said can be witnessed within the below architectural diagram. As shown in the diagram user will be uploading an image from their gallery from a smartphone or the laptop to the application. This image uploaded will be selected as an input to the yolov3 model and the CNN model. They perform their respective process on the image selected and the output obtained is saved within an excel sheet. Along with the output from the model, location-related data obtained is also saved in the excel sheet and this sheet is accessible to the corresponding official.

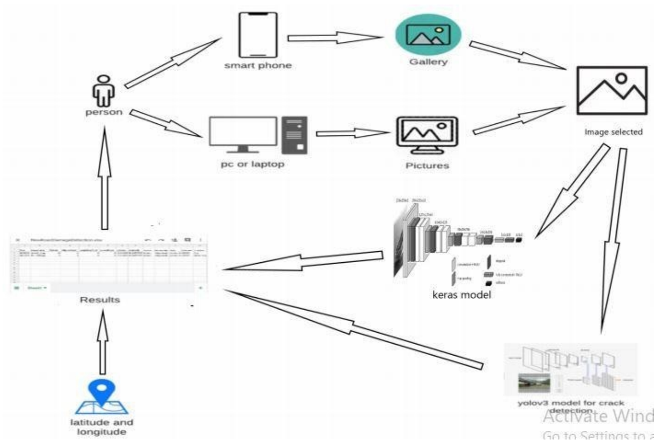

Fig. 4: Architecture diagram

VI. IMPLEMENTATION AND RESULTS

As mentioned earlier a web application is made that is utilized by the user to upload an image and the procedure to be followed for uploading the image and the location details is as below images represent. The web application is made using the Flask web framework in which the Html file of the home page is placed within the templates folder. The templates folder and the static folder are created if they are not already present using the python os command. All the flask required packages are downloaded using the pip command in python. Flask-uploads package is used as it handles the documents, photos, or any other uploads to the flask server efficiently. In the project, this package is made use as road damage image is uploaded by the user.

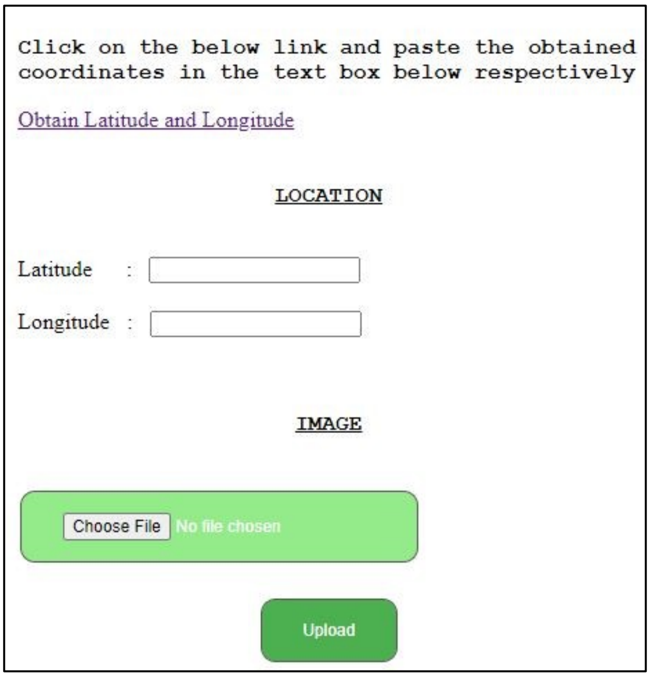

Fig. 5: Upload page

This is the home page of the application which is also the image upload page. The user is asked to provide latitude and longitude details within the location section. If the user is not aware of the latitude and longitude of the area where road damage is found they can use the 'Obtain Latitude and Longitude' website link where road damage is detected. In the image section as seen a choose file button is provided which when clicked asks us to browse through the files within our smartphone or laptop and select the image in jpg format of the road damage and hit the open button.

Fig. 6: Location page

When the link in the upload page is accessed location page is displayed with a single my coordinates button as above. When this button is hit a location access permission dialog box is shown.

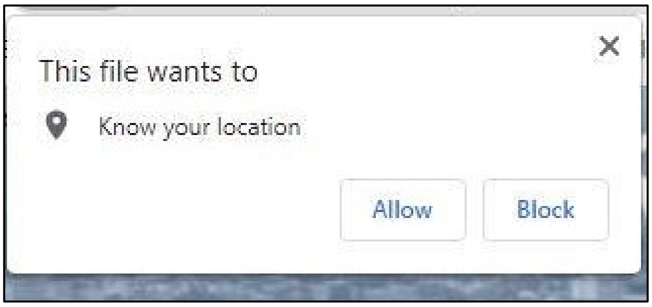

Fig. 7: Location access

This is the dialog box displayed on hitting the button in the location page. User need to select allow option. On selection the block option the location cannot be accessed and corresponding error message is displayed to the user. User can disable the location access granted whenever required in the chrome or the corresponding browser settings page the user is operating on.

Fig. 8: Access denied

The message as in above image is shown when the access to location is denied by the user on selecting block option in the location access dialog box.

Fig. 9: Coordinates

On selecting the allow option in the dialog box the latitude and longitude options are shown as above.
These values can be copied and saved for later use if incase user is not uploaded then and there itself.

Fig. 10: Success page

On completing upload of image and proving location details, upload page looks as shown in above image.

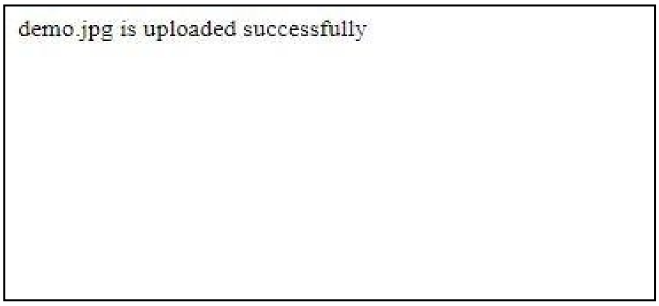

Fig. 11: Success page

When user clicks the upload button in the home page the above message is displayed when the image is successfully uploaded to the flask server.

Date	ImageName	Pothole	AlligatorCrack	LongitdinalCrack	LateralCrack	Latitude	Longitude	District	Muncipality	State	Postcode	Condition
04/18/21	demo.jpg	13	2	0	0	16.48396	80.69102	Krishna	Vijayawada (Urban)	Andhra Pradesh	520001	Poor

Fig.12: Data stored in excel

After all the process of image uploads and coordinates data is done, the results are stored within an excel sheet, for future use. As seen in the above image the demo.jpg image related output is stored in excel as above so that corresponding official can plan accordingly.

VII. CONCLUSION

Road damage caused by the extreme weather conditions, or any other reasons can be solved by the corresponding department mostly in well-known areas and it is even difficult for them to get to know every damage caused in every area. Our project aims to make a model that can detect the type of road crack based on the image uploaded by the user or anyone who encounters the road damage to reduce the time taken due to manual inspection to identify the damage and define the type of crack. With this feature, to beable to define the type of crack and to define the road condition whether it is poor, satisfactory, very poor, and good it will be helpful for the corresponding officials to work on the bad conditioned roads first based on the crack detected and prioritize their work accordingly. Location data obtained in detail is also helpful in prioritizing the work as the officials can know the municipality details and can give the information to them for working on the damage. As a part of future work, we would like to add a language translator so that the details in the websites can be presented based on the language chosen by the user. Even train the model to be able to identify any new cracks possible along with the four types of cracks we can identify now

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