

Civic-Street grievance reporting and monitoring system using transfer learning and usability engineering

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Abstract - Science and Technology have improved the quality of life in many fields. But still, many real time problems are a challenge in addressing public grievance problems to city administrators. This paper proposes an AI grievance image classification model based on artificial intelligence and machine learning. In a developing country like India, people face lots of problems in day to day life. One of them is the garbage or potholes problems on the streets. In most cases many people want to report their problems, but they either don't know where to succeed in, who to contact, lazy to fill an outsized number of forms, no complaint traceability, etc. These problems sometimes take months or even years to get solved if the existing system is followed, there is no proper platform or system to make complaints about the problems and these problems remain unaddressed. Sometimes an individual approaches the local authorities the issues are unheard and there's no record of the complaint.

Keywords — Image classification, Garbage detection, artificial intelligence, grievance, dataset, model training

I. INTRODUCTION

AI citizen grievance monitoring and management model is to solve public grievances such as the garbage, potholes or sewage problem faced by people and help them to reduce it by creating transparent systems and people sourcing. Billions of tons of garbage are generated annually across the globe with almost one lakh metric tons of garbage being generated in India per day. 90% of these wastes cause hundreds of thousands of people to die each year in this developing world.

These problems are causing harm to nature and mankind. Generation of plastic waste is adding a new and harmful dimension to existing problems.

Waste generated by Municipal frequently goes uncollected in poorer countries and rapidly ignites the spread of disease. Around 400,000 and 1 million people are dying due to mismanaged waste. This problem has existed for decades, the growing plastic pollution, which does not decompose easily in the environment unlike Biodegradable Waste, is adding a fresh set of problems to an already dire situation. Plastic waste is obstructing the flow of the water bodies and causing flooding, as a result waterborne diseases are spreading. Burning of waste releases harmful toxins and causes air pollution.

To solve all these issues we have proposed AI grievance monitoring and managing models for solving garbage,

pothole and sewage problems in our country. It is an easy, trackable and transparent complaint management system. It consists of some features like one click reporting where reporting for grievance will take less time than uploading a snap on snapchat and also one will get notified when their problem is solved, so that one can keep track of your problems when your issue is resolved.

II. EXISTING SYSTEM

A. My APCC app

Adar Poonawalla Clean City Initiative is an environmentally sustainable initiative, undertaken by Serum Institute of India and Mr. Adar Poonawalla as a social contribution for the society. The APCCI focus on supporting the Pune Municipal Corporation with collection of street waste, litter picking from footpaths, clearing of chronic waste dumping spots across the city, installing of litter bins at strategic / high traffic locations across the town, support vehicles and manpower for clearance of litter from litter bins.

B. Swachhata app

This application enables a citizen to post a civic-related issue (e.g. garbage dump) which is then forwarded to the corporation concerned and thereafter assigned to the sanitary inspector of the actual ward. An user must take an image of the civic-related issue employing a smartphone and post within the categories given by them. The app can

pinpoint the situation of the complaint with accuracy using the geo-location of the image, which can cause faster resolution of the complaint. Regular complaint status updates - Citizens will get regular updates on the status of the complaint within the sort of a push notification.

III. MODEL OBJECTIVE

Authors developed a model for garbage detection using image classification and machine learning.

Our proposed model uses transfer learning and ResNet model for AI grievance image classification. This model consists of one click reporting of grievances and the user gets notified when their complaints are resolved. The system will automatically notify respective area authorities for solving garbage, potholes or sewage issues on their dashboard. Use of artificial intelligence in classification of grievance type will save user's time and increase their experience by reducing the steps in complaint registration and with better interface.

IV. DESIGN AND IMPLEMENTATION

Modern material design principle based Minimal feature app approach comes with better and efficient user experience saving a lot of time, by just focusing on essential features that are required. The submission of a complaint takes less time than uploading a snap on snapchat. Live tracking of the complaint makes users trust the app and contribute more towards the betterment of the society by using it regularly just like our day to day life. With no process of filling information such as grievance description, address etc makes the approach more viable and easy to use.

Flow and usability of the app:

1. Users can click the picture of the grievance (garbage, pothole or sewage) and raise the complaint on a single click.
2. The App automatically detects the location of the users and the Image processing model in the backend of the app automatically classifies the type of the grievance and hence reduces the tasks at the users end.
3. The acquired information is then notified to the respective area authority on their dashboard from where they can handle the status of the complaints, monitor all the complaints in his/her area with data analysis based metrics based on location, type of grievance and date leading to quick and efficient actions on the complaints.
4. Once the status of a registered complaint is changed, the user is notified about the current status of the app.

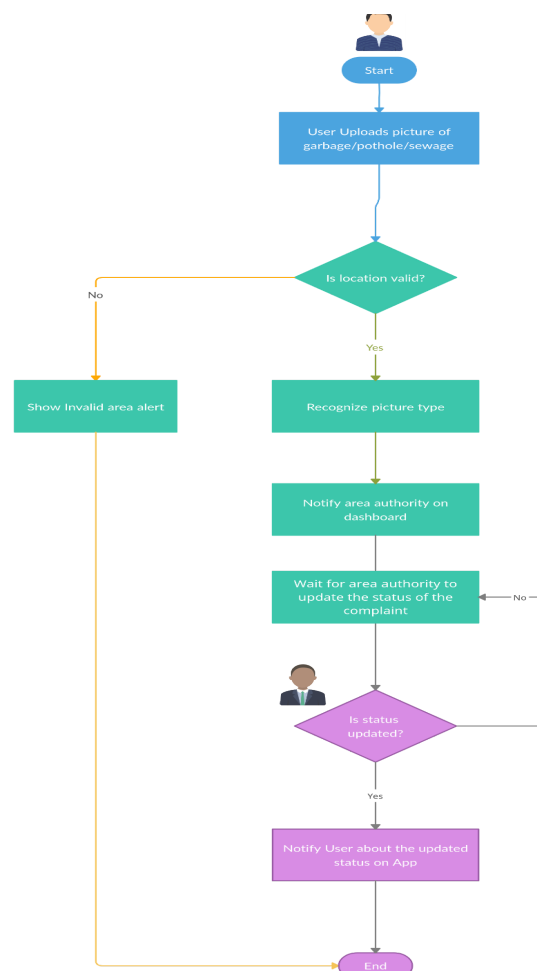


Figure 1: Flow of the app



Figure 2: Camera screen

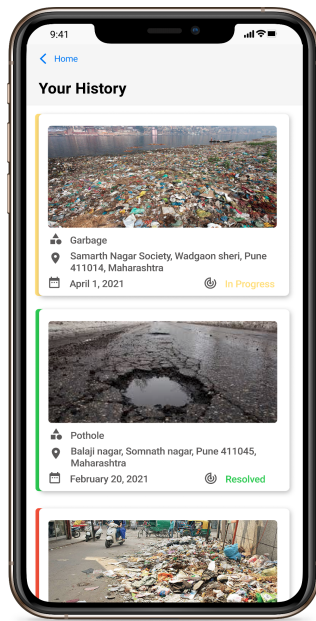


Figure 3: History screen

Minimal feature design approach increases the better usability and better user experience. This could be understood by the Kano model.

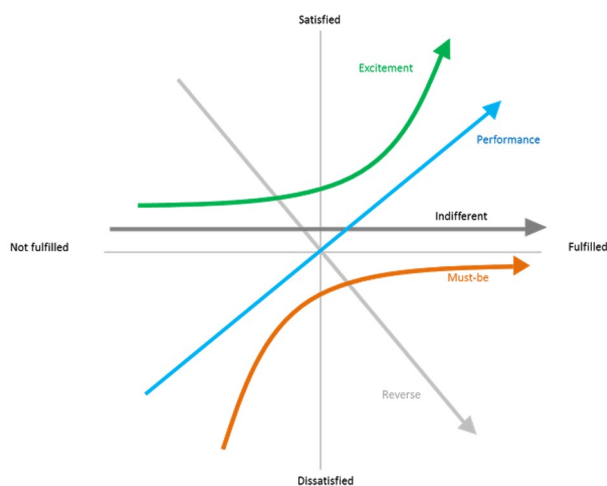


Figure 4: Kano model for product design

V. DATASET DESCRIPTION

A. Data Acquisition

This model was trained on the manually generated dataset of 13,200 images collected from Google images searched and filtered manually on the basis of country so that it could produce better results when trained on Indian images.

Sr No.	Label	Total Images
1.	Garbage	5,000
2.	Pothole	4,200
3.	Sewage	4,000

Table 1: Details of dataset used



Figure 5 : Sample dataset images

B. Pre-processing



Figure 6 : Annotated images using Labeling tool

1. Region of Interest (ROI) segmentation: A ROI or region of interest is a portion of an image which certainly highlights the portion for specific purpose, for example, if we discuss traffic lights, in an image, ROI would be the traffic lights in the image. Similarly in the proposed system, the objective is to highlight the type of grievance (sewages, potholes, and garbage). They are marked in red to differentiate them from the rest of the image. The annotated masks of the grievance, which contained labels '1' for ROI and '0', the unknowns in the dataset, were marked manually. Due to different sizes of the image samples of the dataset, the ROI images were resized and added zero padding to fit into the required input shape for the proposed model which outputted the images with the dimension of 256×256 pixels.
2. Pixel mean - centering: Mean-centering to each of the ROI segmented dataset images was performed because it is an efficient way to understand variation when you are centered at the origin. This process was done by subtracting the mean of all the pixels of an image from all the pixels of that image.

3. Image Normalization: The process of changing the range of pixel intensity value to achieve standardization is called Normalization. Images collected from different sources have different intensity, contrast and different pixel properties thus they need to be standardized.
4. Data Augmentation: Data augmentation is a technique which is widely used in data science to increase the amount of data by adding slightly modified copies of original dataset. Datasets could also be increased by generating synthetic data from existing data. It helps reduce overfitting when training a machine learning model. The augmentation transformations applied on ROI images of garbage and potholes were rotation and flip(mirroring). After augmentation the size of the dataset grew twice the original dataset which was sufficient enough to reach the good accuracy.

C. Transfer Learning Approach

Transfer learning is a machine learning technique where a model trained on one task is re-purposed on another related task. Our image classification model is trained on Convolutional Neural Network based on transfer learning approach. The pre-trained network used in our method is Res-Net 101. ResNet-101 is a deep convolutional neural network which contains 101 layers. Softmax with Adam as the final/output layer, which classifies the input amongst three classes.

D. Proposed Model

The design of ResNets is inspired by the VGG-19 model, based on it the ResNet architecture was made. It was developed for ImageNet (Object detection and Image classification Challenge). In CNN, generally, many layers are connected to each other and are trained to perform different tasks. CNN learns several features at the end of its layers. The convolutional layers' size in this model have 33 filters. In ResNet, every layer has the same number of filters for the same output feature map size and the number of filters is doubled if the feature map size is halved so as to maintain the time complexity for every layer. It does downsampling by convolving layers with a stride of two, which is referred to as Pooling. This ResNet ends with a global average pooling layer and a SoftMax activated fully connected layer. ResNetModule is illustrated in Fig.7. This type of learning i.e. Residual learning can be interpreted as subtraction of input features learned from that previous layer. ResNet does it using sparse connections to each pair of 33 filters, connecting the input of the kth layer to (k+x)th layer. The reason behind bypassing layers is to keep away the problem of vanishing gradients by reusing activations from the preceding layer till the layer next to the present one has learned its weights. While training the network, weights will amplify the layer next to the present one and will also adjust to mute the preceding layer. It has been observed that it is easier to train this network than training simple deep convolutional neural networks. It also resolves the problem of accuracy degradation. ResNet-101 is a 101-layer Residual Network and is a modified version of the 50-layer ResNet.

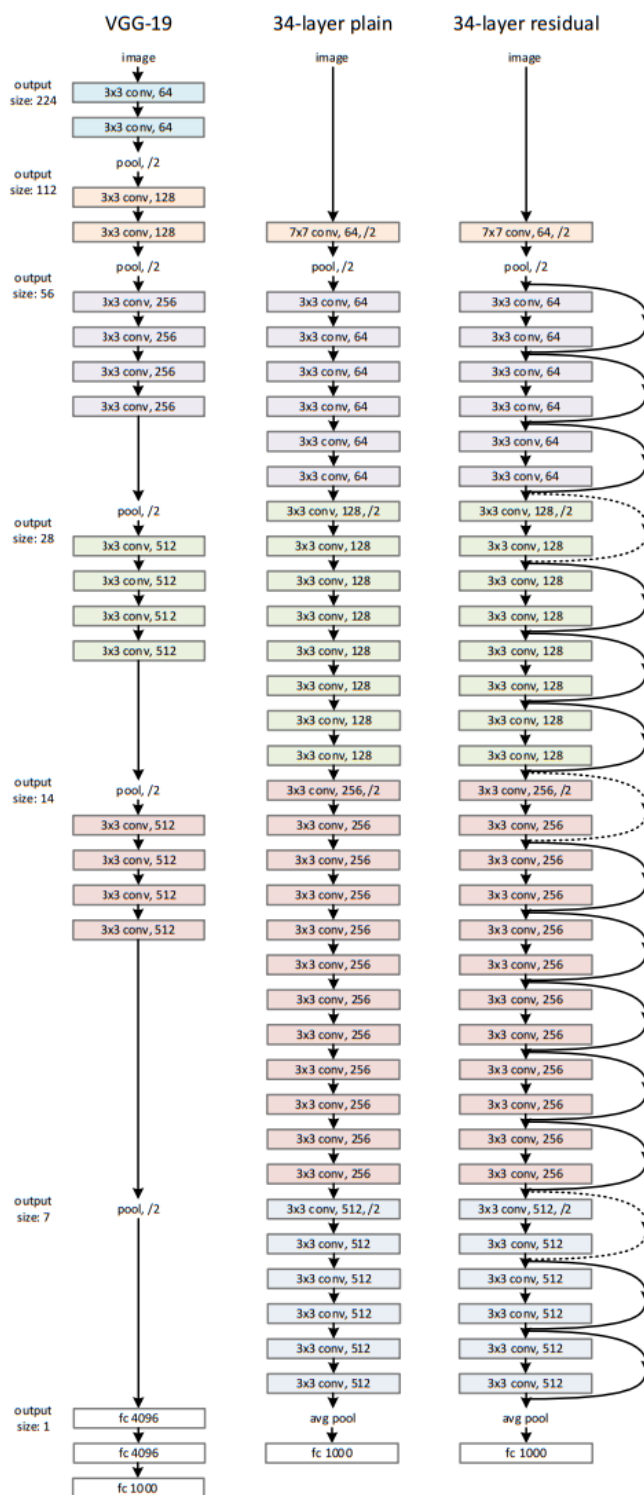


Figure 7 : ResNet 101 architecture

As the depth of the network increases, a degradation problem occurs when deep neural networks start converging leading to saturation in accuracy which rapidly decreases. Adding extra layers to the deep neural network leads to higher training error (overfitting). This can be solved by introducing shortcut connections (skip-connections) that perform identity mappings.

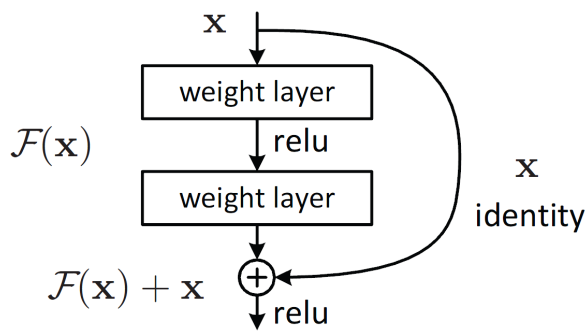


Figure 8 : A Residual Learning Block

Identity mapping, also known as Skip connections, is done by skipping layers in the neural network and feeding the output of one layer as the input to the next layers (instead of only the immediate one). The result is multiplied by a linear projection W to expand the channels of shortcut to match the residual. The input x and $F(x)$ is combined and passed as an input to the next layer.

E. Model training

Dataset contained total images of 31,203 images including augmented images. Dataset was divided into ratios of 70:30 (in terms of percentage) for training and validation sets respectively. Model was downloaded using a fastai **layered API** and trained using the fastai vision library. The original dataset contained images of size $512 \times 512 \times 1$ which were then pre-processed using segmentation methods to generate pictures of dimension $256 \times 256 \times 1$ which focused only on the ROI. We used Adam optimiser to train the model with a learning rate of $1e-02$ at first and then reduced it to $1e-02$ to reduce the loss rate. The preprocessed dataset of images was splitted into 70:30 into training and testing parts. The test dataset was used for evaluating the performance of the model.

F. Evaluation

To evaluate the model generally two things are checked
1. The object present in the image belongs to which class
2. Second the location of the object present in the image.
Precision and recall are the commonly used evaluation metrics for such implementation.
Precision is a ratio of true positive detection to total number of positive detection. With our approach we were able to achieve precision of **98.24%(0.9824)**

$$\text{precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

Recall is the ratio of true positive detection to total number of detection which is the sum of true positive and false negative.

$$\text{recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

Confusion matrix

	Garbage	Pothole	Sewage
Actual Garbage	152	0	0
Pothole	2	123	0
Sewage	4	0	80
	Garbage	Pothole	Sewage

Predicted

figure 9: Confusion matrix

VI. RESULTS

The developed model was able to achieve more accuracy on Indian data which is **98.33%** (+3% by the last accuracy). Using ResNet 101 over ResNet 152 helped us in reducing the size of the developed model by **67%**, previously it was 550MB, then it was reduced to **180MB**.

epoch	train_loss	valid_loss	accuracy
0	0.376654	0.082472	0.980609
1	0.183108	0.060627	0.983379
2	0.116677	0.062730	0.980609
3	0.079540	0.061901	0.983379

Table 2 : Test result

VII. CONCLUSION

Making use of the prior computer technology, we have successfully found an algorithm to be trained in-order to identify the image and developed a process to classify and notify the authority regarding the related issue so that they can resolve it. With an increasing number of garbage issues, cities are getting polluted, increasing potholes and mismanaged sewages. The main goal of our system was to reduce the public grievance problems. Our system provides real time solutions for solving garbage, potholes or sewage problems. Our AI grievance image classification model will help the public as well as the authority members to clean their locality by using our model.

ACKNOWLEDGMENT

We would like to thank Dr. Rekha Sugandhi for her valuable time and constructive suggestions for enhancing the report research work in this article. Also, for her

constant support and efforts in developing the grievance system.

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