DETECTING BUILDING DEFECTS USING CONVOLUTION NEURAL NETWORK

1. INTRODUCTION

1.1 OVERVIEW:

This project deals with detecting the defects and spalls in buildings using Convolutional neural networks. With the help of this project the defects in buildings can be detected conveniently. This focuses on efficient building maintainence with reduced time and labour.

1.2 PURPOSE:

The major purpose of this project is set to investigate the novel application of deep learning method of convolutional neural networks (CNN) in automating the condition assessment of buildings. The focus is to automated detection and localisation of key defects arising from dampness in buildings from images. However, as the first attempt to tackle the problem, this project applies a number of limitations. Firstly, multiple types of the defects are not considered at once. This means that the images considered by the model belong to only one category. Secondly, only the images with visible defects are considered. Thirdly, consideration of the extreme lighting and orientation, e.g., low lighting, too bright images are not included in this project.

2. LITERATURE SURVEY

2.1 EXISTING PROBLEM:

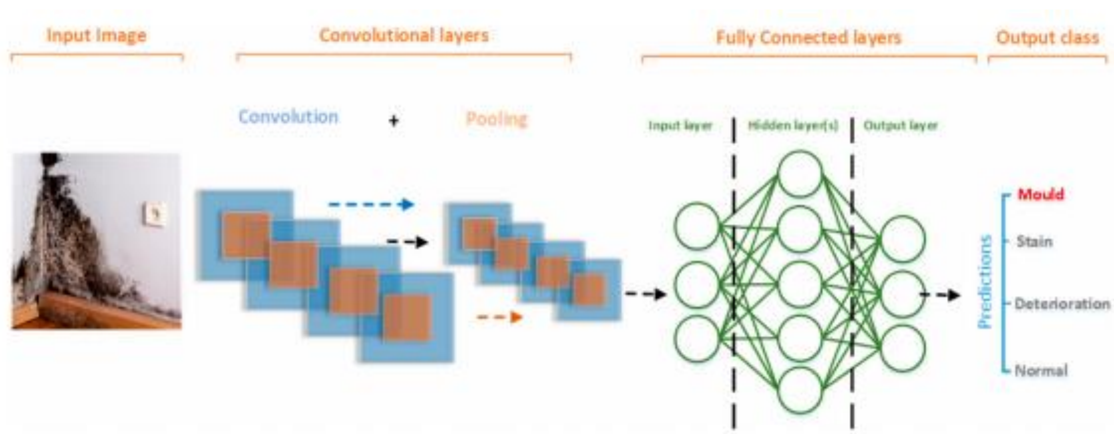
Detection of defects including cracks and spalls on wall surface in high-rise buildings is a crucial task of buildings' maintenance. Clients are increasingly looking for fast and effective means to quickly and frequently survey and communicate the condition of their buildings so that essential repairs and maintenance work can be done in a proactive and timely manner before it becomes too dangerous and expensive. If left undetected and untreated, these defects can significantly a?ect the structural integrity and the aesthetic aspect of buildings, timely and cost-effective methods of building condition survey are of practicing need for the building owners and maintenance agencies to replace the time- and labour-consuming approach of manual survey.

2.2 PROPOSED SOLUTION

This era requires smart buildings. This proposed system is based on pre-trained CNN classifier of VGG-16, with class activation mapping (CAM) for object localisation. The challenges and limitations of the model in real-life applications have been identified. The proposed system has proven to be robust and able to accurately detect and localise building defects. This approach is being developed with the potential to scale-up and further advance to support automated detection of defects and deterioration of buildings in real-time using mobile devices and drones. Where technology takes over manual work of building maintenance. This projects builds an application where it detects cracks and spalls in the buildings and helps in building maintenance.

3 .THEORETICAL ANALYSIS:

3.1 BLOCK DIAGRAM:



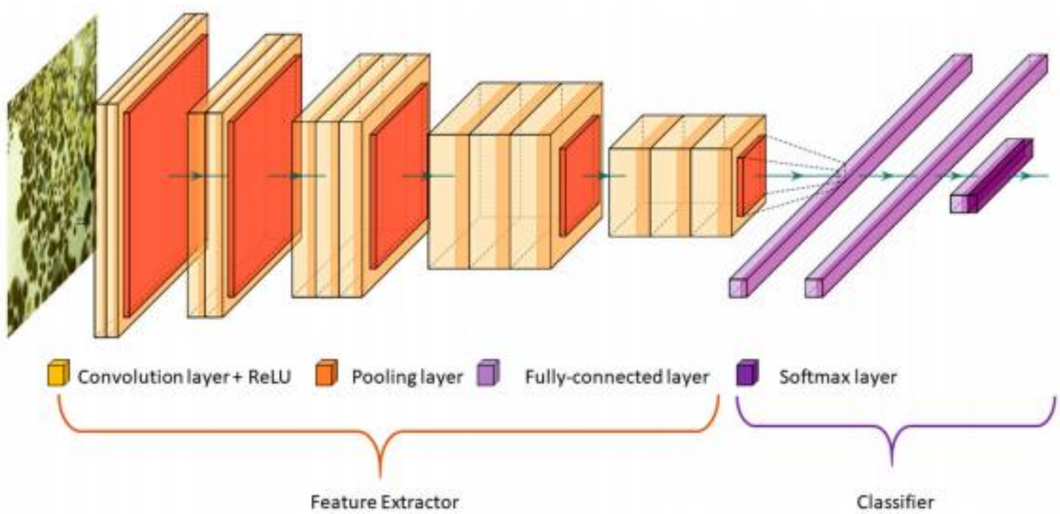


Figure : Deep Learning for detecting buildings.

3.2 HARWARE/SOFTWARE DESIGN:

Hardware Design:

- Hard Disk
- Laptop
- RAM-4GB

Sofware Design:

- Python 3.6
- Jupyternotebook
- Spyder ide

4. EXPERIMENTAL INVESTIGATIONS:

- ### DATA COLLECTION

We have taken images of different resolutions and sizes which were obtained from the internet. The data was labelled into three main categories: mould, stain, and paint deterioration(which include spalling, blistering, flacking, and crazing). The total number of images used as training data was 662. The remaining 202 images out of the 864 were used as testing data with 50 images for each class. A sample of images used is shown in Figures.

- **DATA PREPROCESSING:**

```
from keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(rescale = 1./255,shear_range = 0.2,zoom_range = 0.2,horizontal_flip = True)
test_datagen = ImageDataGenerator(rescale = 1./255)
```

Here we are importing the ImageData generator to train and test the images dataset.

```
]: x_train = train_datagen.flow_from_directory(r'G:\Intern\Dataset Main\train',target_size = (64,64),batch_size = 32 , class_mode =
   x_test = test_datagen.flow_from_directory(r'G:\Intern\Dataset Main\test',target_size = (64,64),batch_size = 32 , class_mode = 'ca

   Found 662 images belonging to 4 classes.
   Found 202 images belonging to 4 classes.
```

```
]: print(x_train.class_indices)

   {'crack': 0, 'flakes': 1, 'roof': 2, 'spalling': 3}
```

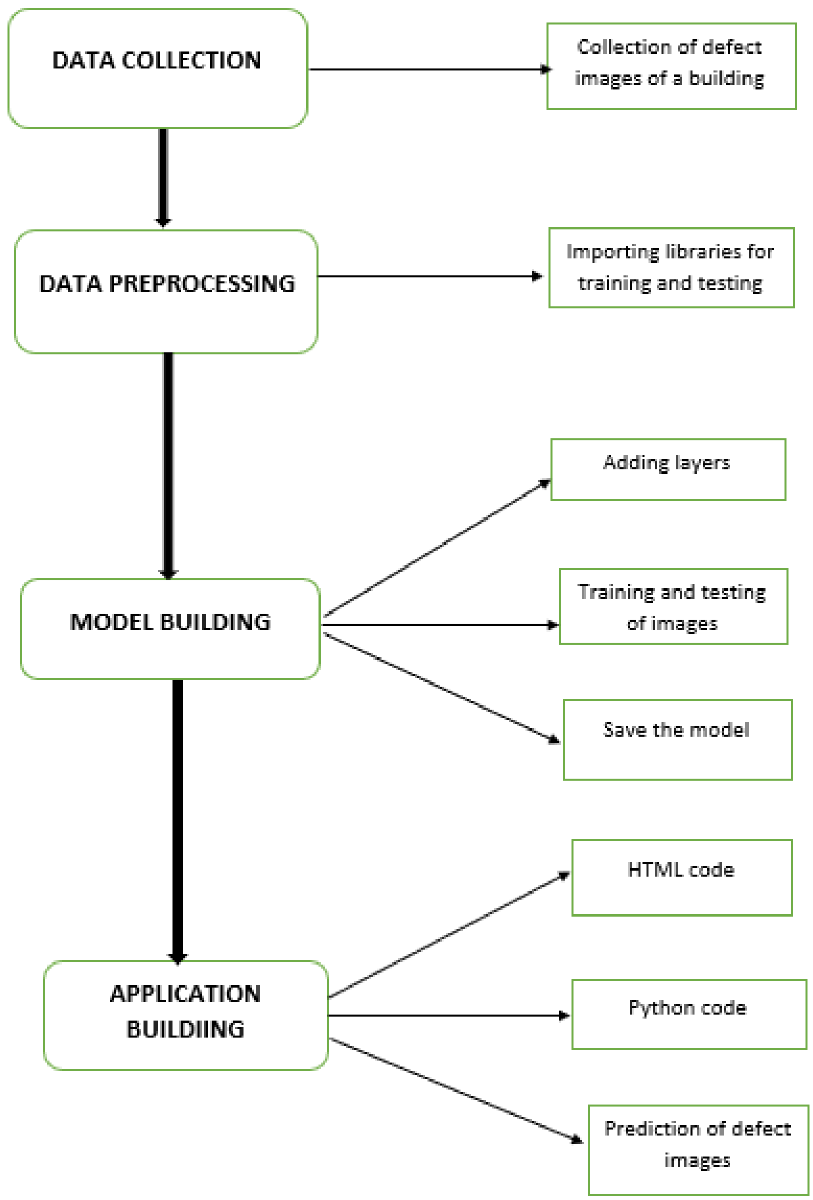
- **MODEL BUILDING:**

    from keras.models import Sequential
    from keras.layers import Dense
    from keras.layers import Convolution2D
    from keras.layers import MaxPooling2D
    from keras.layers import Flatten

The layers are imported along with the activation function for the training and test validation of the images.

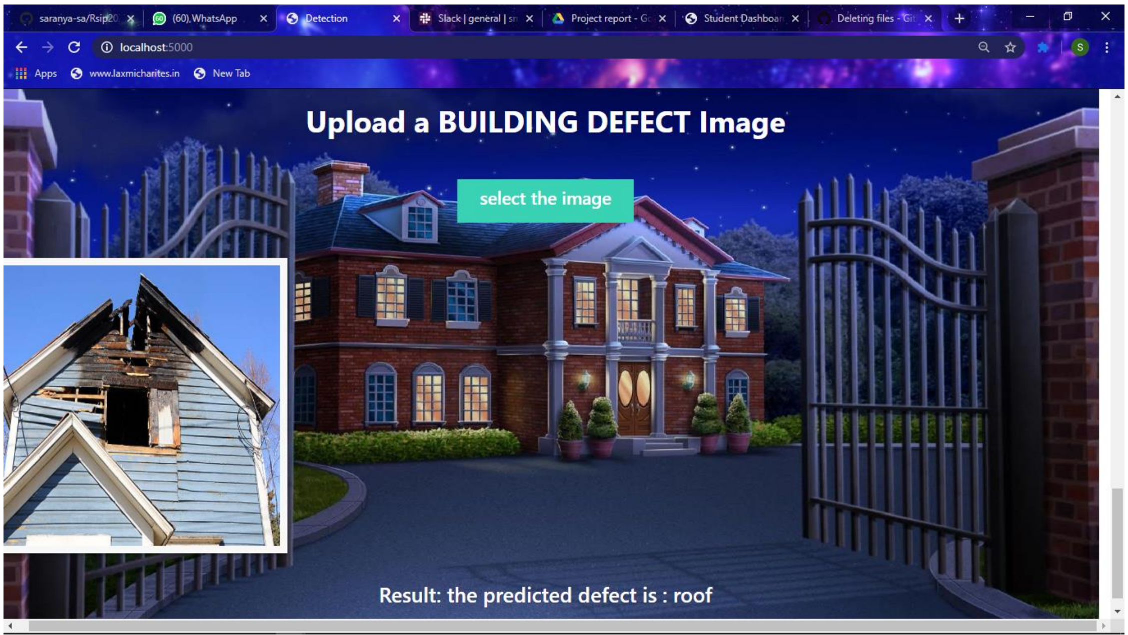
```
: model.add(Flatten())

: model.add(Dense(units=128,init="random_uniform",activation="relu"))

  C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: UserWarning: Update your `Dense` call to the Keras 2 API: `
  Dense(units=128, activation="relu", kernel_initializer="random_uniform")`
    """Entry point for launching an IPython kernel.

: model.add(Dense(units=4,init="random_uniform",activation="softmax"))

  C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: UserWarning: Update your `Dense` call to the Keras 2 API: `
  Dense(units=4, activation="softmax", kernel_initializer="random_uniform")`
    """Entry point for launching an IPython kernel.

: model.compile(loss="categorical_crossentropy",optimizer="adam",metrics=["accuracy"])

  WARNING:tensorflow:From C:\ProgramData\Anaconda3\lib\site-packages\keras\optimizers.py:790: The name tf.train.Optimizer is depr
  ecated. Please use tf.compat.v1.train.Optimizer instead.

  WARNING:tensorflow:From C:\ProgramData\Anaconda3\lib\site-packages\keras\backend\tensorflow_backend.py:3295: The name tf.log is
  deprecated. Please use tf.math.log instead.

: model.fit_generator(x_train,steps_per_epoch=47,epochs=100,validation_data=x_test,validation_steps=20)
```

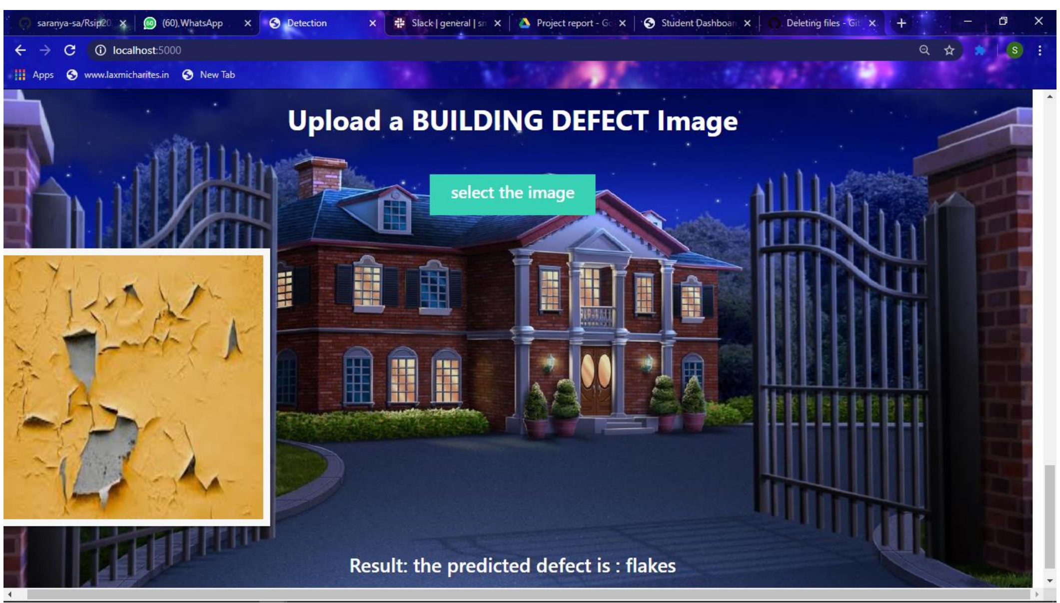
5.FLOWCHART:


DATA COLLECTION
Collection of defect images of a building
DATA PREPROCESSING
Importing libraries for training and testing
MODEL BUILDING
Adding layers
Training and testing of images
Save the model
APPLICATION BUILDIING
HTML code
Python code
Prediction of defect images

6.RESULT:

The network was trained over 100 epochs using batch of size of 32 images and a step of 47 images per epoch. The final accuracy recorded at the end of the 100th epoch was 96.62% for training and 94.83% for the validation . The final loss value was 0.0908 for training and on the validation set 4.5914.





7.ADVANTAGES AND DISADVANTAGES

ADVANTAGES:

1.The main advantage is that it automatically detects the important features without any human supervision.

2. Classification of the defect can be predicted.

3. High reliability and robustness in classifying and localising the defects.

4.Man power for defecting defect is reduced

5.Frequent monerating of any type of defect in the building is reduced.

DISADVANTAGES:

1.There may be slit chances of error while predicting the images

2.Detection is difficult when there so many similar images

3.Classification of images is similar so it is difficult to detect

8.APPLICATIONS:

1. It can be used in detecting the defect in the house.

2.It is very useful in buildings,companies.

3. It is customizable by any type of person.

4. Building can be virtually projected and spots can be defected.

5.The application can be modified for portability in such a way that smart phone cameras can be used to detect the defects or modified for drones for a complete survelience for a defects

9.CONCLUSION:

The work is concerned with the development of a deep learning-based method for the automated detection and localisation of key building defects from given images. This project is part of work on condition assessment of built assets. The developed approach involves classification of images into four categories: three categories of building defects caused by dampness namely: mould, stain and paint deterioration which includes peeling, blistering, flacking, and crazing and of these defects and a fourth category “Normal” when no defects is present. A total of 864 images were used as our dataset. Out of the 864 images, a total 662 images used for training data. In order to obtain sufficient robustness, we applied different augmentation techniques to generate larger dataset. For the validation set, a 20% of the training data (30 images) was randomly chosen. After 100 epochs, the network recorded an accuracy of 96.62% with 0.098 loss on the training set .To address the localisation problem, we integrated the CAM technique which was able to locate defects with high precision. The overall performance of the proposed network has shown high reliability and robustness in classifying and localising defects. The main challenge during this work was the availability of large labelled datasets which can be used to train a network for this type of problem. To overcome this obstacle, we used image augmentation techniques to generate synthetic data for a largely enough dataset to train our model.

10.FUTURE SCOPE:

Future scope is simply focus only on detecting cracks on concrete surfaces which is a simple binary classification problem, we offer a method to build a powerful model that can accurately detect and classify multi-class defects given are latively very small datasets. In the future works, these limitations will be considered to be able to get closer to the concept of a fully automated detection. Through fully satisfying these challenges and limitations, our present work will be evolved into a software application to perform real-time detection of defects using vision sensors including drones. The work will also be extended to cover other models that can detect other defects in construction such as cracks, structural movements, spalling and corrosion. Our long-term vision includes plans to create a large, open source database of different building and construction defects which will support world-wide research on condition assessment of built assets.

11.BIBILOGRAPHY:

- Mohseni, H.; Setunge, S.; Zhang, G.M.; Wakefield, R. In Condition monitoring and condition aggregation for optimiseddecisionmakinginmanagementofbuildings. Appl. Mech. Mater. 2013,438,1719–1725. [CrossRef]
- Agdas, D.; Rice, J.A.; Martinez, J.R.; Lasa, I.R. Comparison of visual inspection and structural-health monitoring as bridge condition assessment methods. J.Perform. Constr. Facil. 2015, 30, 04015049. [CrossRef]