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# R-CNN ResNet-50FPN AND ARTIFICIAL NEURAL NETWORK INTEGRATED WITH NLP TO DETECT SMPS FAULTS

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## Abstract

Deep learning techniques utilize numerous layers of processing to acquire hierarchical data representations and have demonstrated exceptional outcomes in various fields. Lately, within the domain of natural language processing (NLP), there has been an explosion of various model designs and methodologies. The present study employs R-CNN ResNet-50FPN and artificial neural networks for an NLP task and illustrates their progression in automatically detecting faults in SMPS by extracting data from an image. This model enables an individual to input an image of a faulty SMPS, for which Deep learning and Natural Language Processing is used to generate image-based questions and image captions. Using Polling mechanism, the majority of hits will be calculated and based on that the problem identification is fine tuned to top 3 problem category. Then by further questionaries the fault is identified and solution is given.

## Introduction

An SMPS, also known as a switching-mode power supply or switcher, is an electronic power supply that uses a switching regulator to efficiently convert electrical power. It operates by transferring power from a DC or AC source, like mains power, to DC loads, such as a personal computer, while modifying voltage and current characteristics. Unlike a linear power supply, the pass transistor of an SMPS switches between low-dissipation, full-on, and full-off states, spending minimal time in high dissipation transitions, which results in less energy wastage. The SMPS achieves voltage regulation by adjusting the on-to-off time ratio or duty cycles, while a linear power supply regulates the output voltage by dissipating power continuously in the pass transistor. The superior electrical efficiency of the SMPS is a significant advantage over linear power supplies.

When compared to linear supplies, switched-mode power supplies (SMPS) can be significantly smaller and lighter since the transformer can be smaller too. This is because it operates at a high switching frequency ranging from several hundred kHz to several MHz instead of the 50 or 60 Hz mains frequency. However, despite the reduced transformer size, the power supply topology and the requirement for electromagnetic interference (EMI) suppression in commercial designs lead to a greater component count and more complex circuits.

Switching regulators are used in place of linear regulators when higher efficiency, smaller size, or lighter weight is needed. However, they are more intricate and can cause electrical noise issues if switching currents are not carefully suppressed. Additionally, simple designs may have a poor power factor. Failure mode effect analysis is utilized to investigate the over current effects on MOSFET. Several information are gathered from the voltage to verify the health state of the SMPS. A SVM approach assisted by PCA algorithm is used to diagnose the faults was documented in a research paper “Fault Prognostics of a SMPS based on PCA-SVM” by

Yeon-Su Yoo et al. The causes for the failure of semiconductor components used in the power supply design is listed out in this paper. It also briefs on the approaches followed to indicate power supply failure and on the approaches used to avoid false indications in response to transients was discussed by Kiran et al. An online real-time method is presented for predicting the degradation of MOSFETs. First, the relationship between an oscillator signal of source and on-state resistance is introduced. Because oscillator signals change when they age, a feature is proposed to capture these changes and use them as indicators of the state of health of MOSFETs was featured in a research article “Analysis of the Degradation of MOSFETs in Switching Mode Power Supply by Characterizing Source Oscillator Signals” by Xueyan Zheng et al. In “Integrating natural language processing with image document analysis: what we learned from two real-world applications” research article by Jinying Chen et al have utilized NLP and out of vocabulary (oov) name detection to translate the output from Arabic handwriting OCR which lacks reliable sentence boundary markers, and searching named entities which do not exist in the OCR vocabulary, therefore, completely missing from Arabic handwriting OCR output. Similarly in a research article “An Efficient Text-Based Image Retrieval Using Natural Language Processing (NLP) Techniques” by Ashok Kumar P M et al have proposed system concentrates on retrieving image by using the text-based image retrieval system. Text documents are given as input to the preprocessing stage, and features are extracted using TF-IDF. Tom Young et al have reviewed significant deep learning related models and methods that have been employed for numerous NLP tasks and provide a walk-through of their evolution. They have also summarized, compared and contrast the various models and put forward a detailed understanding of the past, present and future of deep learning in NLP. Erinc Merdivan et al have proposed a new approach to natural language understanding in which they have consider the input text as an image and applied 2D Convolutional Neural Networks to learn the local and global semantics of the sentences from the variations of the visual patterns of words. Smriti Sehgal et al had made use of the functionalities of Deep Learning and NLP (Natural Language Processing). Image Caption Generation is an important task as it allows them to automate the task of generating captions for any image. This paper is for people who are visually impaired or suffer from short sightedness. So, rather than looking at an image with trouble they can easily read the caption generated by this model in a larger format.


Interior view of an ATX SMPS:
A: Bridge rectifier;
B: input filter capacitors;
Between B and C: heat sink for switching active components of primary voltage ;
C: transformer;
Between C and D: heat sink for switching active components of at least five secondary voltages, per the ATX specification;
D: output filter coil for the secondary with the largest power rating. In close proximity, filter coils for the other secondaries;
E: output filter capacitors.
The coil and large rectangular yellow capacitor below the bridge rectifier form an EMI filter and are not part of the main circuit board.

**Figure 1. Interior View of an ATX SMPS & its Description**

The possible faults occuring in an SMPS can includes missing of (i) Capacitor (ii) Fan and Heat Sink (iii) Fan heat sink and coil (iv) Fan (v) Heat sink (vi) Heat sink and coil (vii) Ground Disconnected and (viii) OnOff. Based on the possiblity the dataset is created including all these faults into account. SMPS dataset – Missing item folders of the individual parts of the SMPS is present. The image of the defective part is stored under each folder correspondingly.

**R-CNN ResNet-50FPN:**

It is a specific type of convolutional neural network architecture that enhances the accuracy of object detection through the use of a feature pyramid network (FPN). Its development was documented in a 2017 research paper entitled "Feature Pyramid Networks for Object Detection," authored by Lin et al. The abbreviation R-CNN stands for Region-based Convolutional Neural Network, which was initially created by Ross Girshick. This algorithm is part of a group of related algorithms that includes Fast R-CNN and Faster R-CNN, which all work to detect and classify objects in an image. Unlike plain vanilla CNNs, R-CNNs can classify multiple objects in an image by first generating Region Proposals using an algorithm called Selective Search. Fast R-CNN uses Selective Search on the CNN layers to identify Region Proposals, while Faster R-CNN uses a specialized object detection algorithm that enables the CNN to learn the Region Proposals itself. ResNet is a type of artificial neural network that is designed to resemble the structure of pyramidal cells in the brain. This type of neural network uses skip connections or short-cuts to jump over certain layers to improve its performance. A typical ResNet model includes double or triple-layer skips with ReLU nonlinearities and batch normalization in between. HighwayNets are ResNet models that use an additional weight matrix to learn the skip weights, while DenseNets are models with several parallel skips. ResNet 50 is a specific CNN model provided by the Keras library, which includes 50 layers.

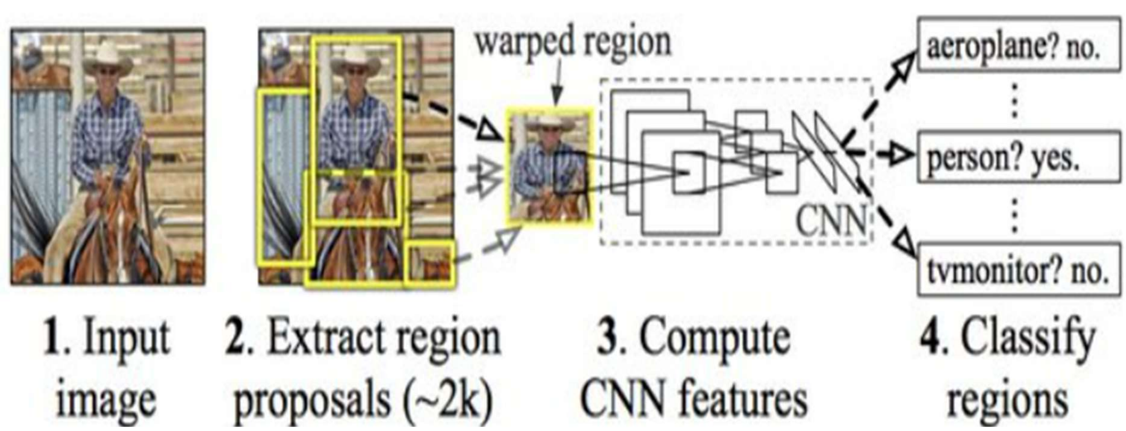



**Figure 2: R-CNN: Regions with CNN features**

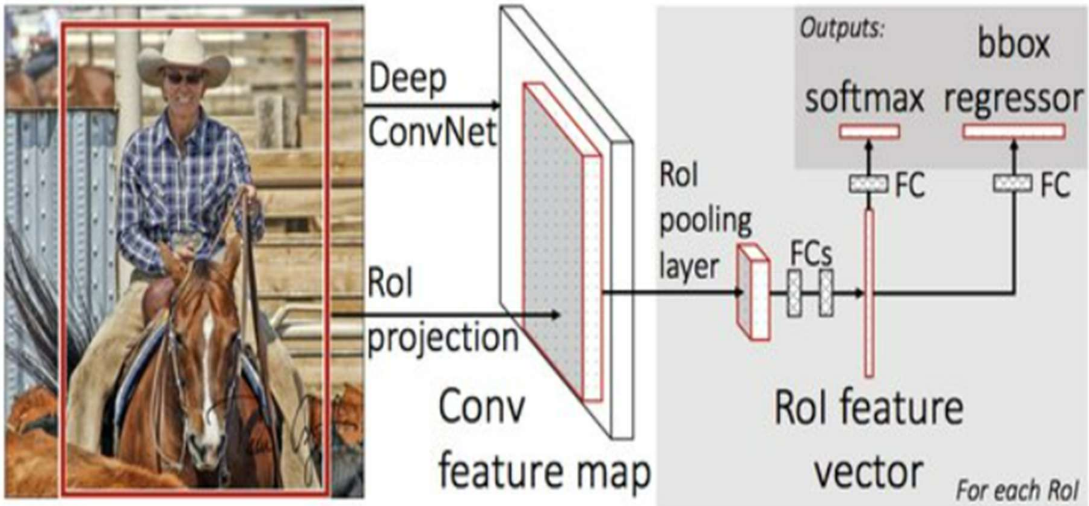



**Figure 3: Fast R-CNN**

ResNet is a type of neural network architecture that has enabled the successful training of extremely deep networks consisting of 150 or more layers, which was previously difficult due to the problem of vanishing gradients. Essentially, ResNet is a pre-trained convolutional neural network model that is specifically designed for computer vision tasks and aids in training such models effectively. Convolutional neural networks (CNNs) are primarily used for classifying images by assigning them to different categories. On the other hand, an R-CNN (with "R" standing for region) is designed specifically for detecting objects within an image. While a typical CNN can identify what objects are present in an image, it cannot determine where exactly they are located. Although it's technically possible for a CNN to estimate bounding boxes for individual objects, it struggles when multiple objects are present, resulting in interference. To address this limitation, R-CNNs are structured to process one region at a time. The selective search algorithm is used to detect the different regions within an image, which are then resized to a consistent size before being passed through the CNN for classification and bounding box estimation. By focusing on individual regions, R-CNNs minimize interference and improve object detection accuracy.

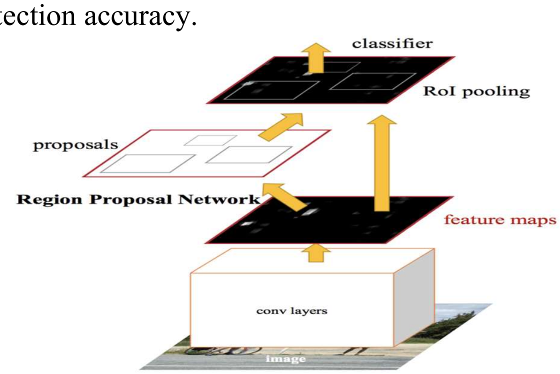



**Figure 4:Faster R-CNN**

**Artificial Neural Network:**

Neural networks are a form of artificial intelligence that utilize a deep learning approach to teach computers how to process data in a way that mimics the human brain. They employ a layered structure of interconnected nodes, or neurons, which closely resembles the structure of the human brain. In essence, neural networks are a machine learning technique that attempts to replicate the brain's ability to process and learn from information. An artificial neural network is a collection of interconnected nodes that are designed to simulate the function of neurons in the brain. Each node within the network represents an artificial neuron, and connections between the nodes are represented by arrows that carry information from one neuron to another. In this way, the artificial neural network mimics the way that information flows through the brain's neural networks. Similar to synapses in a biological brain, each connection within an artificial neural network has the ability to transmit a signal to other neurons. An artificial neuron receives these signals, processes them, and can then signal to other neurons that it is connected to. The signal at each connection is a numerical value, and the output of each neuron is determined by a non-linear function that is based on the sum of its inputs. These connections are referred to as edges, and both neurons and edges have an associated weight that is adjusted during learning. This weight determines the strength of the signal transmitted at each connection and can either increase or decrease based on the learning process. In addition, neurons may have a threshold that must be crossed in order for a signal to be sent. Neurons are typically grouped into layers within the network, and different layers may perform distinct transformations on their inputs. Signals flow from the input layer (the first layer) to the output layer (the last layer), with the possibility of traversing the layers multiple times.

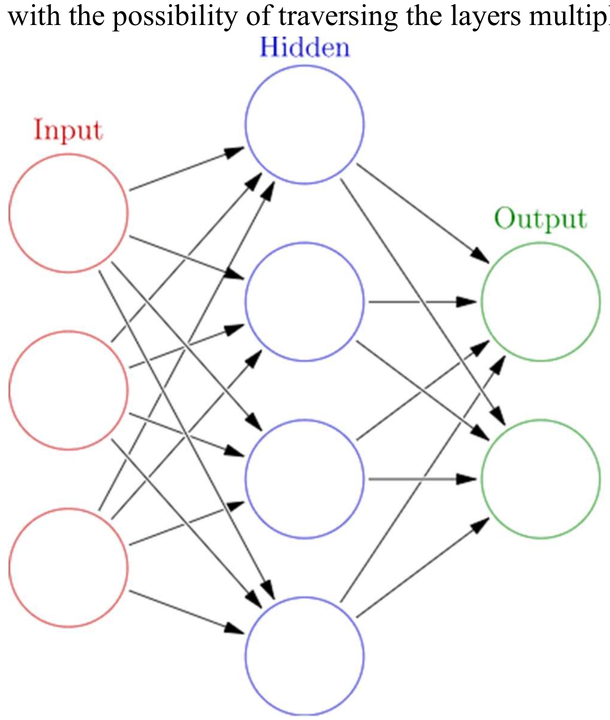



**Figure 5: Artificial Neural Network Model**

**Methodology:**

R-CNN ResNet-50FPN is a powerful object detection algorithm that excels at identifying and localizing objects within an image. By integrating it with an artificial neural network, we can improve its ability to classify objects and increase the accuracy of its predictions. The neural network can learn to recognize patterns within the data that may not be immediately apparent to the R-CNN algorithm alone, improving its ability to distinguish between similar objects. Furthermore, the neural network can also help to optimize the performance of the R-CNN algorithm by providing feedback on its predictions. By adjusting the weights of the network during training, we can improve the accuracy of the R-CNN algorithm and ensure that it is detecting objects as accurately as possible. Overall, the integration of R-CNN ResNet-50FPN and an artificial neural network offers a powerful solution for improving computer vision. By combining the strengths of these two algorithms, we can create a highly accurate and efficient system for object detection and classification.

**Steps involved**

1. To create a model we are using Co-Lab
2. Dataset for the SMPS is created (Convert it to XML file and connect it with HTML category.

Each image has these details mentioned below

a) Location of the folder
b) File name
c) Image name
d) Path
e) Width
f) Height
g) In X and Y axis what defect is present?
h) ROI- based on the X &Y position it is created.

3. Faster R- CNN ResNet-50FPN & ANN is employed to identify and localize an object within an image.
4. Connected to the drive to fetch the dataset.
5. Connecting dataset by navigating the path
6. List the content in the folder
7. Convert XML to CSV (comma seperated value)

| | filename | width | height | class | xmin | ymin | xmax | ymax | image_id |
|---|---|---|---|---|---|---|---|---|---|
| 0 | IMG20221127141057_BURST008.jpg | 1800 | 4000 | Capacitor | 897 | 1469 | 1089 | 1608 | 0 |
| 1 | IMG20221127141057_BURST009.jpg | 1800 | 4000 | Capacitor | 893 | 1477 | 1021 | 1594 | 1 |
| 2 | IMG20221127141057_BURST010.jpg | 1800 | 4000 | Capacitor | 877 | 1492 | 987 | 1598 | 2 |
| 3 | IMG20221127141057_BURST011.jpg | 1800 | 4000 | Capacitor | 900 | 1531 | 1087 | 1684 | 3 |
| 4 | IMG20221127141057_BURST012.jpg | 1800 | 4000 | Capacitor | 921 | 1545 | 1035 | 1648 | 4 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 172 | IMG20221127151348_BURST019.jpg | 1800 | 4000 | ONOFF | 716 | 2125 | 758 | 2214 | 47 |
| 173 | IMG20221127151348_BURST020.jpg | 1800 | 4000 | Heat Sink | 1128 | 1824 | 1712 | 1991 | 48 |
| 174 | IMG20221127151348_BURST020.jpg | 1800 | 4000 | Coil | 1230 | 2008 | 1605 | 2215 | 48 |
| 175 | IMG20221127151348_BURST020.jpg | 1800 | 4000 | Capacitor | 819 | 2345 | 892 | 2439 | 48 |
| 176 | IMG20221127151348_BURST020.jpg | 1800 | 4000 | ONOFF | 714 | 2123 | 780 | 2218 | 48 |

177 rows × 9 columns

**Figure 6: Conversion to CSV file**

8. Matplot lib is used to print the image in the python environment

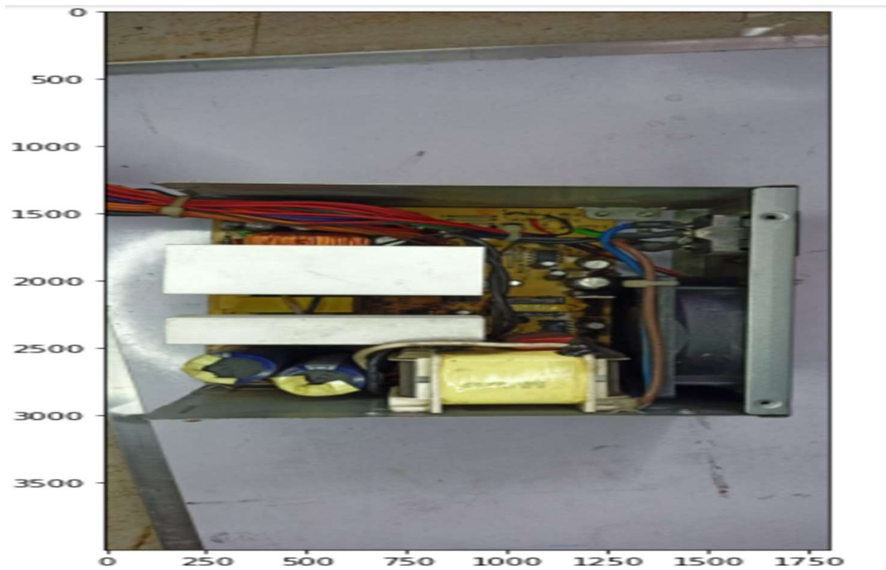



**Figure 7: SMPS image printed in python environment**

9. Torchvision – image is transformed to CSV + normal image JPEG which eventually produces a computer vision image.

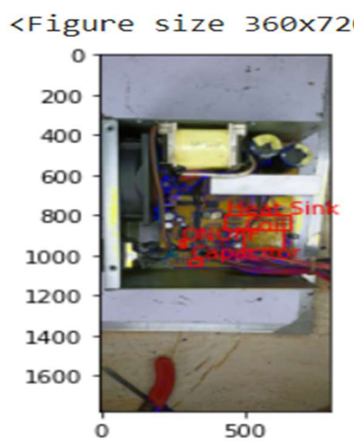



**Figure 8: Computer visualized image using the proposed model**

10. Augmentation on the image is performed
11. Using the Faster R- CNN ResNet-50FPN & ANN we are visualizing the image
12. The algorithm helps to narrow down the search for the missing region with the label.
13. Dataloader: It will create a trained Dataset (All CSV + normal mixed image)
14. Validation Data – Reference of XML file is taken for test which is initially converted as test and train CSV file)
15. Based on Deeplearning training the model is performed (classifier fit)
16. 1 epochs = 1 feedforward +1 back propagation . we have performed 20 epochs to detect the fault from the given image.

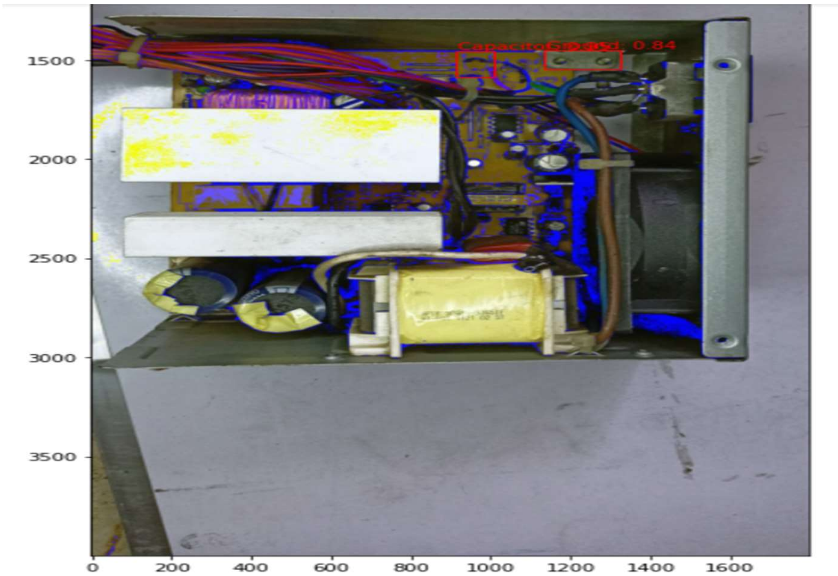
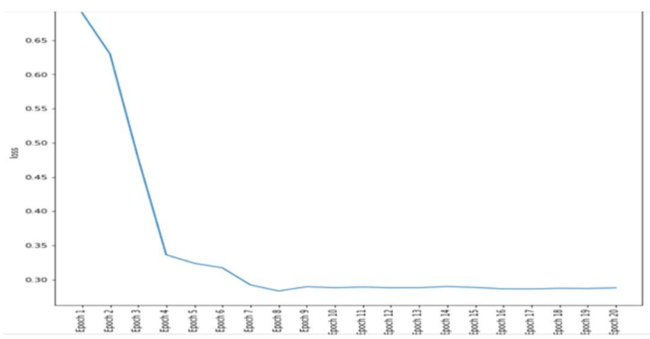



**Figure 9: Fault Detected by the proposed model**

- Initial epoch -69% loss
- Final epoch – 28 % loss
- 73% accuracy model




```
[0.6903914354589521,
 0.629836225996212,
 0.4775347069514041,
 0.3362501391342708,
 0.3238033780029842,
 0.317154017182029,
 0.29216713853636567,
 0.28333035978127497,
 0.2896039791557254,
 0.2881245068749603,
 0.2891516019495166,
 0.2880243549541551,
 0.2881620123374219,
 0.2898813037543881,
 0.2885284743138722,
 0.28641715584969035,
 0.28633896687201094,
 0.2872271496726542,
 0.2869168668985367,
 0.28786199752773556]
```

**Figure 10: Accuracy at each Epochs**

17. Pycharm behaves as a server and it is connected to the browser.
18. Streamlit package -chatbot in browser
19. It will go to the local host (any port with an ID)

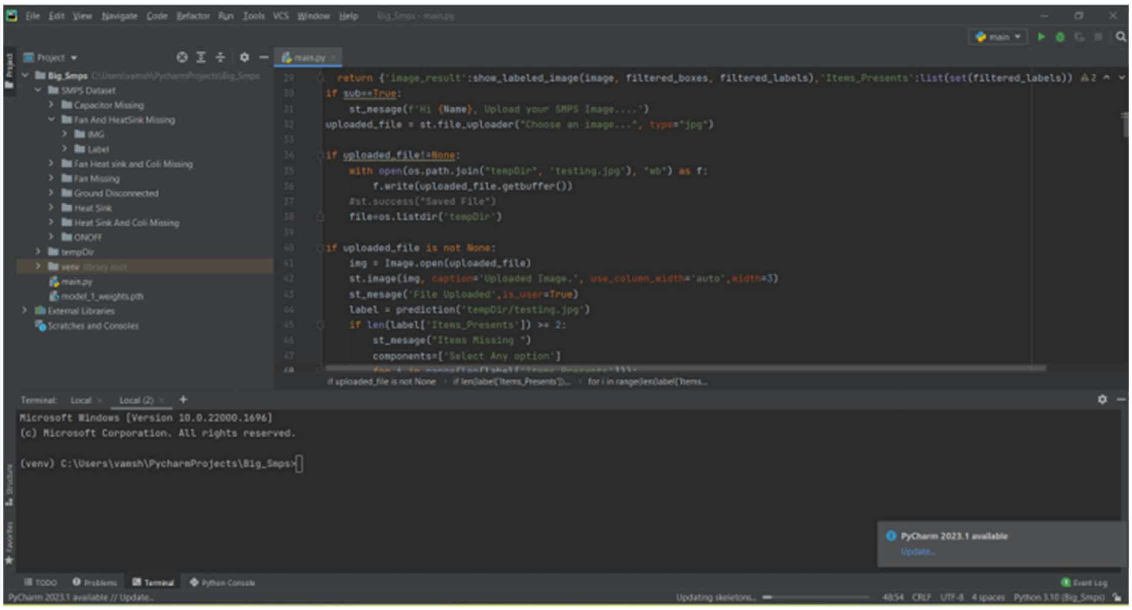



**Figure 11: Pycharm community**

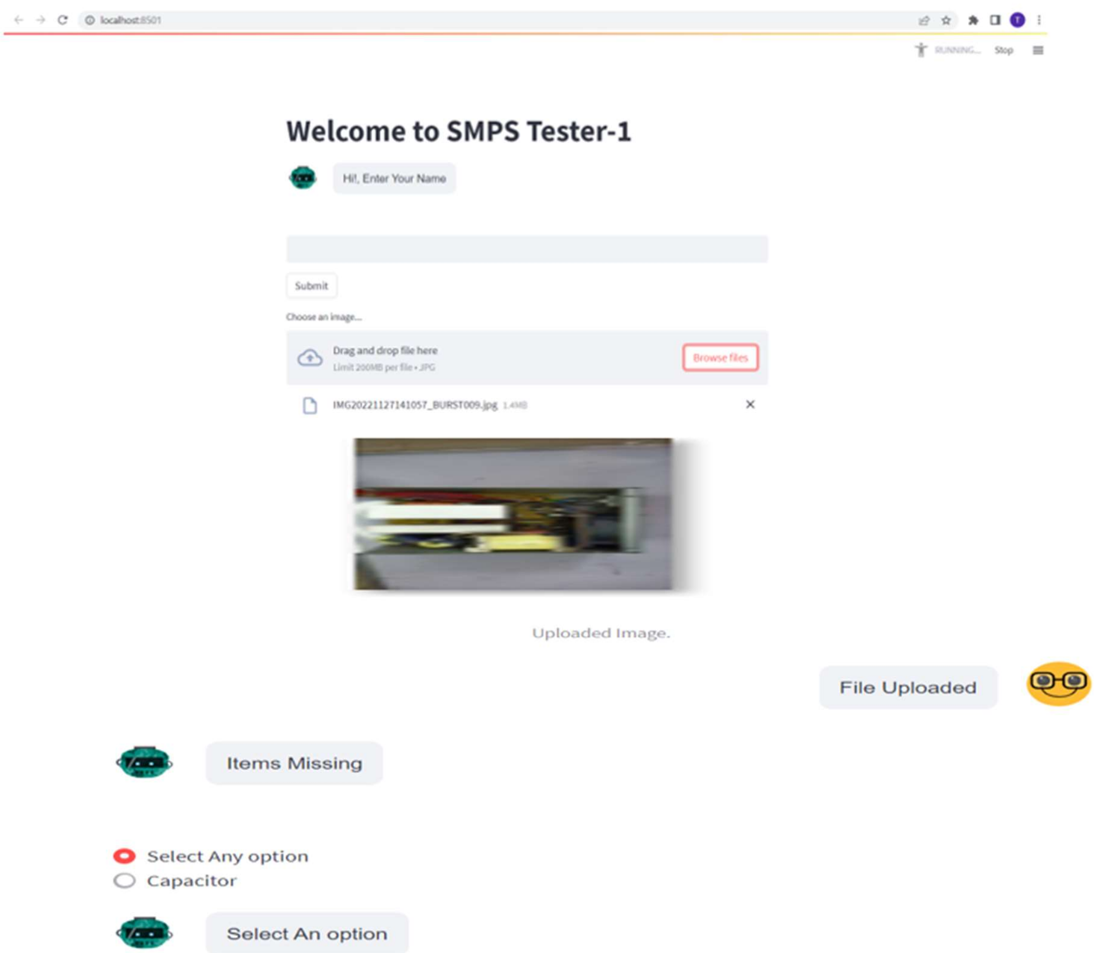



**Figure 12: Chatbot Frontend**

This is the client for the server local host 8501. Test data is given and question is rised automatically. From the above figure it is noticed that it has identified the missing part and it as given as an option. Further based upon the client request it will provide an appropriate solution.

**Conclusion**

A NLP based chat box is designed using python. The faulty SMPS image is given as an input. Based on the image the questions are generated. Using the polling mechanism the highest hit is calculated and the top three problem statements are highlighted. With further questions and the answers received the fault is detected from the three highlighted problem statement. Faster R- CNN ResNet-50FPN & ANN is employed to identify and localize an object within an image.It improves the computer visualization model. Deep learning approach helps to self [5acts like a server. The python program acts as a backend for the chat bot. 245 images were used for training and 100 images were used for testing the model. The proposed model works efficiently and it self learns each and everytime from the feedback it receives from the client based on the request and questionaries raised.

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