



AI Enabled Self Diagnosis Predictor Tool Using Tongue Image Capture with Automatic Prescription Generation

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AI ENABLED SELF DIAGNOSIS PREDICTOR TOOL USING TONGUE IMAGE CAPTURE WITH AUTOMATIC PRESCRIPTION GENERATION

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ABSTRACT

WHO data shows that half of the people in the world suffer due to basic health care needs as there are not enough medical facilities available in many parts of the world. It is difficult for the refugees to have all the basic health care needs and not enough doctors available for primary diagnosis. To diagnose the person there are many methods by which the doctor can predict what type disease one might be suffering from. One of those factors includes the first diagnosis done by just observing the tongue, as it's the only visible part of the body and one of the factors which helps for primary diagnosis and widely accepted by doctors in TCM, diagnosis. It addresses for an aid to people to do primary diagnosis from tongue using AI device, like Raspberry Pi with camera, which is trained using tongue dataset of different types of tongue images like strawberry tongue, Black tongue, normal tongue, Red tongue, Swallowed tongue etc. for various symptoms of various diseases to identify the type of the tongue and based on that it will generate the prescription. The proposed research work is based on the edge computing and does not need any internet or cloud support and best suitable for installing as portable kiosk in affected areas where primary medical facility is not available. The report generated by system has primary predicted suggestions based on the tongue diagnosis using AI

KEYWORDS

ICT in Health, Artificial Intelligence, Primary Diagnosis, Health prediction, Edge Computing

1. INTRODUCTION

To diagnose the health of a person there are lots of factors through which the doctor can predict what the disease might one be suffering from. One of those factors include the diagnosis done by just looking at the tongue as it's the only visible part of the digestive system and hence can predict the overall health of the body as well. The tongue describes overall health of the body system and metabolic and nutritive health of a person. Change in tongue's texture, color, shape, size can predict the disease one might be suffering from and also predict which body part might be affected due to it. The Chinese medicine, Ayurveda and Greek physicians also have considered the tongue as a important predictor for diagnosing the body at first instance. These days thermometers are found in every home just to measure the temperature to primarily understand the body temperature and helps to do self-diagnosis at primary level, The same way if an AI enabled system can help us to understand the human tongue type, one can easily do self-diagnosis which can help a person to visit doctors in time before the diseases grows much. There are places in the world where people do not have enough medical facility to monitor their health as there are no doctors available. Hence, to overcome that difficulty an AI enabled health

predictor system can be made so that just by clicking the picture of the tongue the machine will be able to predict through transfer learning method of machine learning, what sort of disease a person might be suffering from and might suggest to consult a doctor for further diagnosis. The system does claim about specific diseases but surely gives a list of possible health problems one might be suffering from giving details about, the type of the tongue and based on that it will generate an automatic prescription which contains the accuracy, type of tongue and predicted possible health problem, later it will be easier for the doctor and the patient for diagnosing the disease it will also helpful for the doctor in making the diagnosis process easier as it is generated by a trained AI model using thousands of data.

2. METHODOLOGY

There are various tongue related ways to identify the disease a person is suffering from. The tongue is supposed to be the starting point for diagnosing the patient's health. The prediction is based on various factors which includes the color, textures, and the surface of the tongue. There are various types of tongue except from the anomaly tongue like based on the textures are the Geographical Tongue, Fissure Tongue based on colors there is Yellow, tongue, Red or Angry tongue, Purple tongue, Magenta Black or Hairy Tongue. Depending on the color texture and features of the tongue the prediction is done on the basis of the same. Also, the tongue is considered as a map according to the Chinese medicine which describes that the tip of the tongue is connected to the, the back is connected to the kidney the sides to the liver. Depending upon the different types of tongue the person's health can be predicted. If the person has red spot on the side of the tongue it might result a person suffering from cancer or HIV, red color suggests that a person might be suffering from acute fever, magenta color describes the deficiency of riboflavin, strawberry tongue represents a scarlet fever or an acute fever hence just a looking a patients tongue the doctor is able to predict what sort of disease a person is suffering from hence the same concept here is applied to train the machine in a similar way.

2.1. Dataset Preparation

As in for the prototype version of the system the samples of tongue have been obtained varying from color, texture, shape and size. They have been labelled as fissured tongue, hairy tongue, normal tongue, HIV etc. and sorted out the images accordingly. After classifying manually, the types of tongue were given as labels. Improper and blur images were removed. Different images of tongues were kept in different folders as labels as shown in figure 1

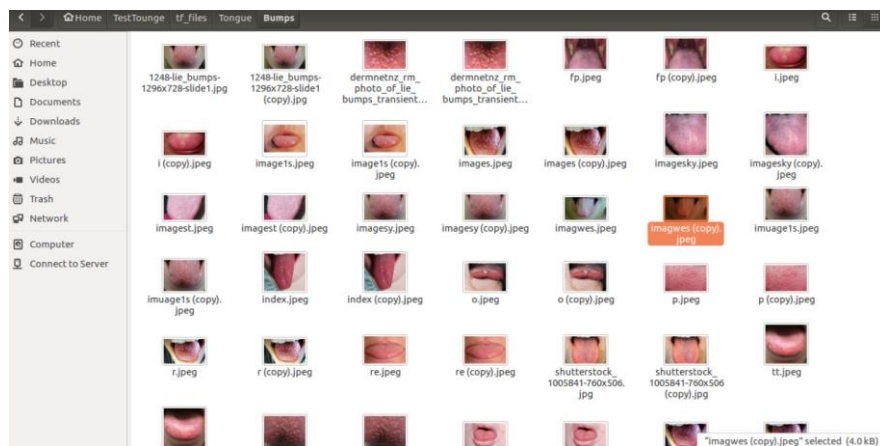


Figure 1 Samples of tongue images collected.

Now the images are kept in the respective folder for their purposes, which are supposed to be done through the Raspberry Pi shown in figure Now the dataset is ready for being trained by the Inception model as shown in figure 5 using transfer learning, which is the pre-trained model in which the last layer of the CNN has been trained and due to that the model is trained by the concept of Transfer Learning using Raspberry Pi and deployed. Here are some of the samples of various types of tongues based on color, texture, shape and size as shown in figure 2, 3 and 4



Figure 2: Fissured Tongue (R) Strawberry Tongue (L)

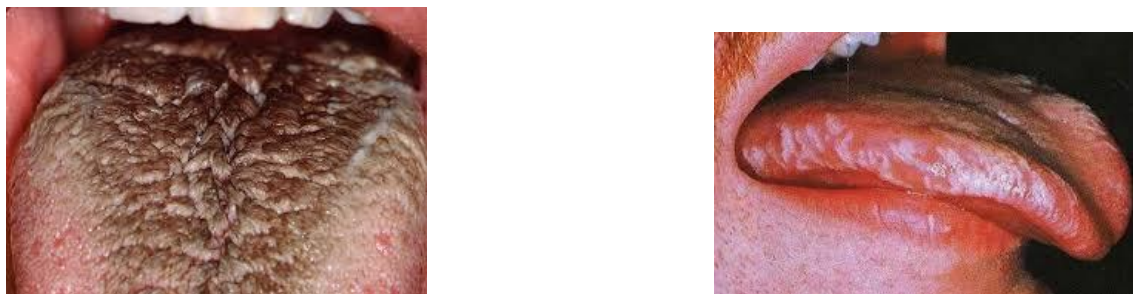


Figure 3: Hairy Tongue (L) HIV Infected Tongue (R)



Figure 4: Geographical Tongue

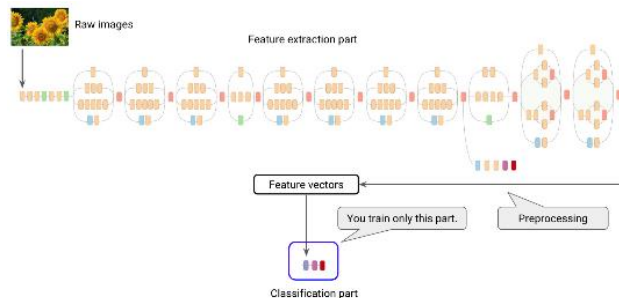


Figure 5 : Inception Architecture Source :Google colab

Now the model obtained after the dataset which has been trained properly and is ready for testing for a Health Prediction system using the Raspberry Pi 3

2.2. Setting up Raspberry Pi 3 and making an AI model using TF Lite



Figure 6: Downloading the Inception Model Figure 7: Raspberry Pi 3

The bottlenecks that will be created are shown in the below figure, which represents the number of counts of the layers that have been trained for the model. The greater number of bottlenecks created more number of layers are present hence the model has been trained accurately.

```
INFO:tensorflow:2019-07-15 22:27:55.193734: Step 320: Cross entropy = 1.052725
INFO:tensorflow:2019-07-15 22:27:55.246050: Step 320: Validation accuracy = 74.0 % (N=100)
INFO:tensorflow:2019-07-15 22:27:55.764717: Step 330: Train accuracy = 80.0%
INFO:tensorflow:2019-07-15 22:27:55.764883: Step 330: Cross entropy = 1.043612
INFO:tensorflow:2019-07-15 22:27:55.815772: Step 330: Validation accuracy = 66.0 % (N=100)
INFO:tensorflow:2019-07-15 22:27:56.312218: Step 340: Train accuracy = 77.0%
INFO:tensorflow:2019-07-15 22:27:56.312392: Step 340: Cross entropy = 1.015363
INFO:tensorflow:2019-07-15 22:27:56.362693: Step 340: Validation accuracy = 80.0 % (N=100)
INFO:tensorflow:2019-07-15 22:27:56.846482: Step 350: Train accuracy = 68.0%
INFO:tensorflow:2019-07-15 22:27:56.846610: Step 350: Cross entropy = 1.096826
INFO:tensorflow:2019-07-15 22:27:56.895942: Step 350: Validation accuracy = 69.0 % (N=100)
INFO:tensorflow:2019-07-15 22:27:57.372975: Step 360: Train accuracy = 65.0%
INFO:tensorflow:2019-07-15 22:27:57.373107: Step 360: Cross entropy = 1.135699
INFO:tensorflow:2019-07-15 22:27:57.420077: Step 360: Validation accuracy = 62.0 % (N=100)
INFO:tensorflow:2019-07-15 22:27:57.901820: Step 370: Train accuracy = 71.0%
INFO:tensorflow:2019-07-15 22:27:57.901986: Step 370: Cross entropy = 1.097720
INFO:tensorflow:2019-07-15 22:27:57.948755: Step 370: Validation accuracy = 67.0 % (N=100)
```

Figure 10: Re training of the inception model

```
dhwani@dhwani-Vostro-14-3468: ~/FE
File "/usr/lib/python2.7/urllib.py", line 98, in urlretrieve
return opener.retrieve(url, filename, reporthook, data)
File "/usr/lib/python2.7/urllib.py", line 245, in retrieve
fp = self.open(url, data)
File "/usr/lib/python2.7/urllib.py", line 213, in open
return getattr(self, name)(url)
File "/usr/lib/python2.7/urllib.py", line 350, in open_http
h.endheaders(data)
File "/usr/lib/python2.7/httplib.py", line 1053, in endheaders
self._send_output(message_body)
File "/usr/lib/python2.7/httplib.py", line 897, in _send_output
self.send(msg)
File "/usr/lib/python2.7/httplib.py", line 859, in send
self.connect()
File "/usr/lib/python2.7/httplib.py", line 836, in connect
self.timeout, self.source_address)
File "/usr/lib/python2.7/socket.py", line 557, in create_connection
for res in getaddrinfo(host, port, 0, SOCK_STREAM):
IOError: [Errno socket error] [Errno -3] Temporary failure in name resolution
dhwani@dhwani-Vostro-14-3468:~/FE$ sudo python scripts/retrain.py --output_graph
=/home/dhwani/FE/tf_files/retrained_graph.pb --output_labels=/home/dhwani/FE/tf_
files/retrained_labels.txt --image_dir=/home/dhwani/FE/tf_files/FACS --architec
ture mobilenet_1.0_224
>> Downloading mobilenet_v1_1.0_224_frozen.tgz 30.6%
```

Figure 11: Downloading the Mobilenet Architecture

To see the training and the testing accuracy it is shown in the below table.

Table 1: Testing and Train Accuracy

| Steps | Train Accuracy (%) | Test Accuracy (%) |
|-------|--------------------|-------------------|
| 1 | 34% | 20% |
| 2 | 67% | 50% |
| 3 | 94.12% | 95% |

When the model will be trained, there will be two files that will be created in the Tongue folder known as retrained_graph.pb and retrained_label.txt These two files represent the values that has been obtained after retraining the model through our model and the one which will have names of the labels that we have labelled accordingly. The size of the retrained_graph.pb is 171MB.

```
dhwani@dhwani-Vostro-14-3468:~$ sudo python scripts/retrain.py --output_graph=/home/dhwani/TestTounge/tf_files/retrained_graph.pb --output_labels=/home/dhwani/TestTounge/tf_files/retrained_labels.txt --image_dir=/home/dhwani/TestTounge/tf_files/Tounge --architecture mobilenet_1.0_224
```

Figure 12: Generation of retrained_graph.pb and retrained_labels.txt

```
dhwani@dhwani-Vostro-14-3468:~/FE$ gzip -c tf_files/rounded_graph.pb > tf_files/rounded_graph.pb.gz
dhwani@dhwani-Vostro-14-3468:~/FE$ gzip -l tf_files/rounded_graph.pb.gz
compressed      uncompressed    ratio uncompressed_name
4627762         17112148       73.0% tf_files/rounded_graph.pb
```

Figure 13: Compressing the retrained file obtained to the optimized file.

```
dhwani@dhwani-Vostro-14-3468:~/FE$ python -m scripts.quantize_graph --input=tf_files/optimized_graph.pb --output=tf_files/rounded_graph.pb --output_node_names=final_result --mode=weights rounded
dhwani@dhwani-Vostro-14-3468:~/FE$
```

Figure 14: Conversion of retrained_graph.pb to rounded_graph.pb (optimized_graph.pb)

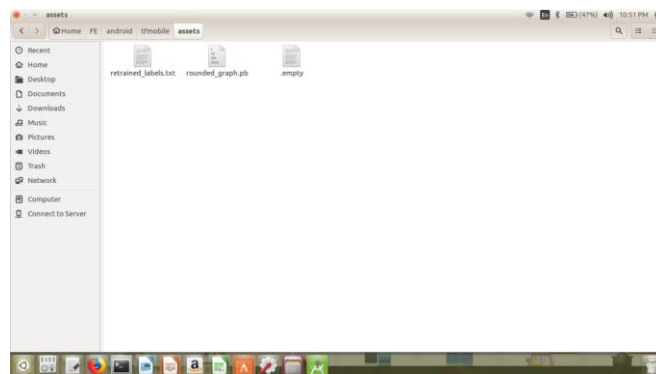


Figure 15: The retrained file and the label file generated in the tf_files folder.

3. GENERATION OF PRESCRIPTION

Using PyPDF python library to generate pdf file, the automatic prescription is generated from Raspberry Pi and sent to Telegram messenger application. The pdf file contains the photo of the tongue under diagnosis and symptoms are added as labels in the file. The screenshot of the telegram is shown in the figure 16.

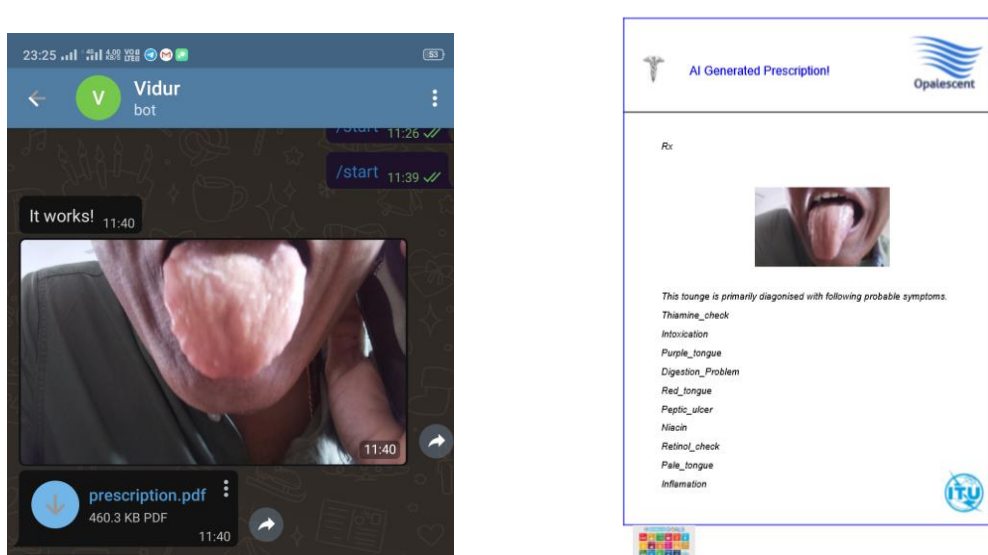


Figure 16 Telegram messenger and autogenerated pdf

4. FUTURE SCOPE

This system can be useful for the people that do not have enough facilities especially in underdeveloped countries where there are no doctors available for the primary diagnosis using this app the patient will be able to predict what disease he might be suffering from and as the app does not require any internet connectivity hence it will be really helpful. Technology Aided healthcare device might be a boon for both the doctors and the people who do not have enough facility for basic health treatment and AI might be helpful in saving lots of lives.

5. REFERENCES

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