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Disaster Prediction And Post Disaster Management Using Machine Learning And Bluetooth

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Abstract

Convolution Neural Network (CNN) is shadow-resistant, capable of getting proper disaster characteristics, and, most importantly, capable of overcoming operator misdetection or misjudgement, all of which have an impact on the system's efficacy. Training and testing are the two phases of the neural network. By clipping and resizing aerial pictures acquired from Kaggle, pre- and post-disaster training data patches are created. Focusing on Hurricane's Pacific Ocean Training dataset, which contains 4387 train photos. All patches are trained in CNN to extract disaster regions occurred without delay. The technique will detect disasters with an accuracy of 80-90%. An off-grid communication system is created with the help of a scatternet based on Bluetooth. This will help in establishing communication between various affected groups and can help in spreading the information faster to the authorities and rescue teams. The app will create the network required for communication among groups and the authorities and the website will display all the collected data to the concerned authorities. It will help in increasing the connectivity between affected people at the disaster location. It will allow the relief management team to have an upper hand by enabling them to contact the people in the affected area.

Keywords Hurricane's Pacific Ocean Training dataset; Scatternet; Relief management

Introduction

Disaster is an undesirable occurrence caused by forces largely beyond human control that strikes quickly and without warning, causing or threatening serious disruption of life and property, including death and injury to a disproportionately large number of people, and necessitates mobilisation of resources far beyond those normally provided by statutory emergency services (Laws and Prideaux, 2013). Natural disasters, in comparison to natural dangers, are more immediate and result in large-scale, widespread death, property damage, and disruption of social structures and life over which individuals have little or no influence (Toya and Skidmore, 2007). As a result, any occurrence will be classified as a disaster if it causes a large amount of devastation and damage.

Warnings and predictions can save lives(Fakhruddin, Kawasaki and Babel, 2015). People can act to protect themselves from injury and death with only a few minutes' notice of a disaster. Disaster forecasting may also help to reduce economic and damage losses. Natural resources and property are protected when notification of an imminent disaster is provided long in advance, as it is for a few wildfires, hurricanes and riverine floods.

And to minimize the damage or loss of lives in the aftermath of a disaster, it is very important that

rescuers are able to track the location of the disaster to perform coordinated relief efforts immediately.

Communication is playing a vital role in any kind of situation in our day to day life, ranging from sitting at our home during quarantine and practising work from home or being stuck in a disastrous situation. Depending on the level and intensity of the disaster, the conventional options and solutions could be partially or completely destroyed. As a result, the impacted area's internet connectivity has been lost, and they are effectively cut off from the rest of the world until the calamity is discovered through other methods.

The use of Internet of Things with post-disaster administration is indeed a problem that has yet to be solved. The Internet of Things (IoT) is a prospective technology that can help tackle some of the issues outlined above.

“The main benefit of using this technology is that it can be easily integrated with other household devices, so the problem of carrying any other devices is also solved. Taking advantage of this point, the project we are intending to make does not require any other device. To extend its range or to handle more cases a repeater or an extender can be used with it, but with the advancement in the Bluetooth technology, even that extender is not needed, the latest version of Bluetooth in use is providing a range of 100m(in ideal situations).”

Literature Review

The technique proposed (Aqib, Mehmood and Albeshri, 2018) the use of GPUs to cater to compute the intensive nature of DL algorithms. To the simplest of our understanding, they're the primary to apply a deep learning (DL) approach in the disaster management. They used the real-world open road traffic within a city accessible in the United Kingdom (UK) Department of Transport. Our outcomes demonstrate the effectiveness of deep -learning approach in disaster management & proper prediction of traffic behaviour in catastrophe situations using VANET (Vehicular ad hoc network), Deep Learning, GPU (Graphical processing Unit), Computational Neural Network (CNN) Predict traffic catastrophe in emergency situation with accuracy of 96.543. Survey informed (Mosavi, Ozturk and Chau, 2018) that Floods are the most common natural disasters that are difficult to model, and Machine Learning models were tough-stoned through a chemical analysis of robustness, accuracy, effectiveness, and speed, which were specifically investigated to produce an in-depth overview on various ML algorithms used in the domain. The performance comparison of Machine-learning models presents an in-depth understanding of various techniques within the framework of global evaluation by using Deep-Learning, Artificial Neural -Networks (ANNs), Multilayer-Perceptron (MLP), Adaptive Neuro-Fuzzy Infer-ence System (ANFIS). We concluded that it compares all the DL and ML algorithms to conclude that which of the following is the best algorithm technique, best of them are Artificial Neural Networks with an accuracy of 90 to 95.

The methodology (Singh, Saraswat and Faujdar, 2017) proposed the use of numerous machine-learning algorithms which are Logistic-Regression, Naïve Bayes Algorithm, Decision-Tree (DT), Random Forest to forecast the survival of the passengers. Specifically, we try to contrast these algorithms by using Naïve Bayes Algorithm, Logistic-Regression, Decision-Tree (DT) & Random forest. Thus, it is concluded that Logistic Regression manifested to be the best algorithm for Titanic classification problem with an accuracy 93.54% as a result.

Author proposed (Shakya, Kumar and Goswami, 2020) a DL-based approach, a feasible candidate for Auto-matic image processing, which requires large sets of elucidated data with diverse characteristics for priming purposes. We've employed interpose and data augmentation techniques for intensification of temporal resolution & diversifications of characters in an exceedingly provided dataset. For categorization purposes, a Keras model was edified on the dataset using Deep-Learning. We came to the conclusion that the photos obtained from KALPANA-I were downloaded from the (IMD), and the model was edified on 6930 augmented photographs and validated by 2970 images, with a model accuracy of 90%.

The research (Centre, 2021) draws an inference that the model used convolutional layers to improvise a pattern to glance, as well as fully-connected classifier to forecast whether a tropical cyclone is contemporary in the input using Deep Learning Algorithm. The dataset used was ERA-Interim from January 1979 until the July 2019 and the model obtained an accuracy of 99.08%.

Research (Wu et al., 2020) was based on deep-learning (DL) & is proposed by prospecting the distribution custom of atmospheric & oceanic elements. 3D-CNN, to learn the implicit correlation between the spatial distribution characteristics of 3D environmental variables and Tropical Cyclone intensity change using technologies like Three-dimensional convolutional neural network, Image processing technology and Data augmentation. Analysis datasets of the western North Pacific for 22 years (1997-2018) was selected in this study and the model obtained an accuracy of 96%.

Technique proposed (Zhou, Xiang and Huang, 2020) a new skeleton of deep-learning neural-network (GC–LSTM), which is predicated on info of spacecraft-cloud pictures. The Graph Convolution-al Network (GCN), is employed to process the irregular contiguous structure of spacecraft cloud pictures beneficially as well as Long STM (LSTM) network is employed to find out the traits of satellite cloud pictures over time, using various algorithms like Deep-learning(DL) neural network, and Graph Convolutional–Long Short Term Memory Network (GC–LSTM). The dataset contains above 1000 typhoon processes and the model provided an accuracy of 95.12%.

The methodology proposed (Zhang et al., 2019) an ML framework which is thrived to work out whether the MCS algorithm would emit into a tropical cyclone. Additionally, the ML classifier proposes that the low-level whirl & genesis potential-index are the foremost important predictors to Tropical Cyclone genesis which is according to former discoveries using algorithms like Machine learning framework, Importance of predictors, GPI classifier, and Performance metrics. We looked into Performance of GPI threshold classifier, Machine learning classifiers, Importance of predictors and concluded that the AdaBoost classifier achieves an accuracy of 97.2%.

Researchers drew (Khalaf et al., 2018) an inference regarding capacious research indicating that AI algorithms could be fabricated enhancement when employed for the pre-processing of torrent data. These proposals helped in acquiring finer accuracy within classification techniques, using novel ML algorithms, Neural Network Architectures and Artificial intelligence. They came to a conclusion that flood dataset, which comprises over 2000 annotated swamp events, provided an accuracy 90%.

Ad-hoc Network Formation

Authors (Sarkar et al., 2017)did an analysis on creating an ad hoc network with the help of vehicles that can communicate with each other and can deliver information at a larger distance through the network. The authors advocated that a strong post-disaster management framework be built around network development and peer-to-peer communications.

A new algorithm for the required formation is illustrated that discusses vital enabling IoT methodologies and uncovers IoT-based post-disaster reaction and recovery. The paper helped in understanding the real-life uses of IoT.

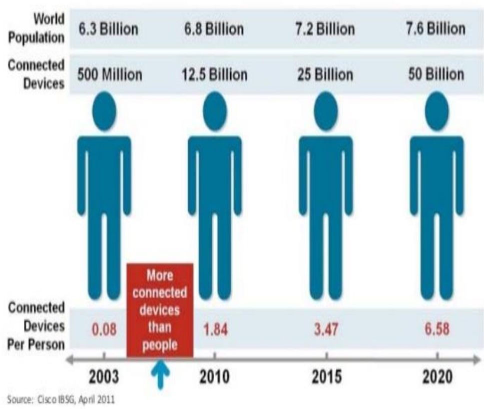

Fig 1 Growth of connected devices
Source: [Cisco IBSG, April 2011]

Deploying Wireless Sensing Network (WSN)

Researchers (John Wellington and Ramesh, 2018)in their report of course project discussed the usage of WSNs in disaster management. They introduced a unique architectural approach for productive catastrophe management that uses the Internet of Things to mitigate the impact of a disaster.

By connecting the Wireless Sensing Network and the internet through a getaway and deploying it can create an emergency basis routing system to lessen the death rate. Using smart city monitoring devices, it is possible to acquire a vast amount of data to design a disaster management system that can work effectively.

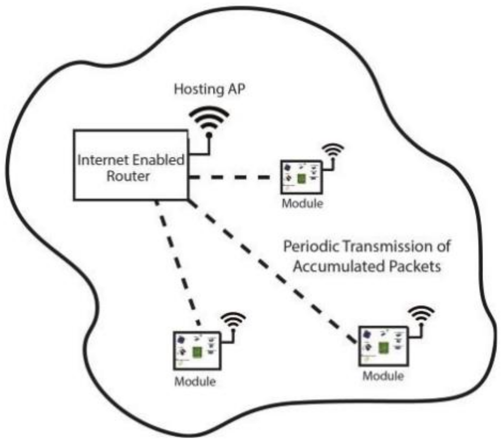

Fig 2 WSN with Android [Source: Researchgate.net]

Use of LPWA Technology

Methodology (Sinha, Wei and Hwang, 2017) focused on the adoption of LPWA (Low Power Wide Area) technologies Narrow Band (NB)-IoT and Long Range (LoRa) are two of the most popular LPWA technologies. Unlicensed LoRa has been found to have an advantage in terms of battery capacity, capacity, and cost. A wireless telecommunications wide area network that allows for long-distance communication that can also help in reducing power consumption along with lower operation cost.

The LoRa WAN network is used to adapt modulation techniques with multichannel multi-modem transceivers to receive a large quantity of signals from the channels in the ground station In the LoRa modulating technology, the needed data bit rate, chirp rate, and symbol rate are associated as follows:

The LoRa modulation bit rate R_b

$$R_b = SF * \frac{1}{\left[\frac{2SF}{BW}\right]} \text{ bits/s}$$

Where SF = spreading factor, BW = modulation bandwidth (in Hz).

SSFX Algorithm for Scatternet

Methodology (Methfessel, Peter and Lange, 2011) introduced the SFX algorithm is used to create a scatter-net tree for an auto and conscience network that may be used with real Bluetooth nodes. The method is based on previously reported SHAPER algorithms, but it includes important features such as time synchronisation, visibility of nodes, and concurrency consideration. The algorithm comprises of four major steps -

1. Basic tree-merging procedure
2. Locking and loop avoidance
3. Tree optimization
4. Tree self-healing

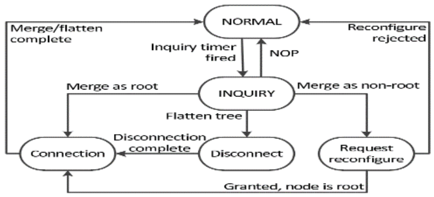

Fig 3 State machine for the merging node Source: [docs.nomagic.com**]**

A survey (Indexed et al., 2021) of the various strategies employed by users for the goal of mitigation and management is offered. Following that, a comparison is made based on the findings of a study conducted to determine the preferred choice of users, which revealed that nearly 90% of users favoured a mix of Cloud - based IoT technologies. A poll conducted by bain is also shown, which reveals the percentage of the people who support the usage of IoT in research. Disasters result in various types of diseases in the survivors like skin diseases (Deep and Techniques, 2021). Data collected from disastrous location even help in getting lost ancient culture (Chadha, Mittal and Singhal, 2020).

Methodology

Data Description: The satellite images were collected from Kaggle. The raw imagery consists of more than 10500 image strips. It was captured using optical sensors with sub-meter resolution, then pre-processed (including ortho-rectification and atmospheric adjustment) and pan sharpened by the image supplier. Some of the strips overlap, resulting in black pixels in the overlapped area. Clouds also obscure some photographs completely or partially. Some images which were of low quality (for the stance of model training) were chosen to discard.

Damage Annotation: Architecture begins with raw data and ends with undamaged annotation output. The first stage is to use a cropping window method to transform the raw data into training-ready data. After that, the cropped photos are carefully screened to assure the dataset's excellent quality. The images are then cleaved into training, testing and validation sets so as to feed them to a convolution-al neural network.

Data Processing: A track of all the available coordinates and use a semi-automated procedure is kept to ensure that each one is linked to a distinctive, "good-quality" image in the final dataset.

Data Featurization: Sizes of the window based on the distance is determined, there may be a round-off mistake when transforming the distance to number of pixels. As a result, both are estimated onto the feature dimension.

Image classification: Dataset is unbalanced because of the restricted accessibility of pre-event photos and the elimination of some images (e.g., due to cloud covering) in the Damaged and Undamaged categories.

Data Storage: As soon as there is internet access to any of the devices present in that scatternet network, that device will send the request to the server. The request will include the coordinates of that device. Once the request is made, this data will be stored on the server. All the devices in the network which will be having internet access will similarly send their location. A database is also maintained so that we will only be sharing the data of the affected people, only to the authorities concerned with that area.

Data Representation: The request will be made by the Admin End which is also our Representation Module. This request will be met with a list of points that were impacted by the disaster. If we observe closely then we will get to know that these locations we are receiving will be forming the boundary (convex hull in terms of Graph) of the area where communication is lost. This convex hull is also shown at the admin end, and the data points which are lying inside the convex hull will be removed from our collection of points. This data can also be plotted on the graph to get an accurate representation of the area affected by the disaster.

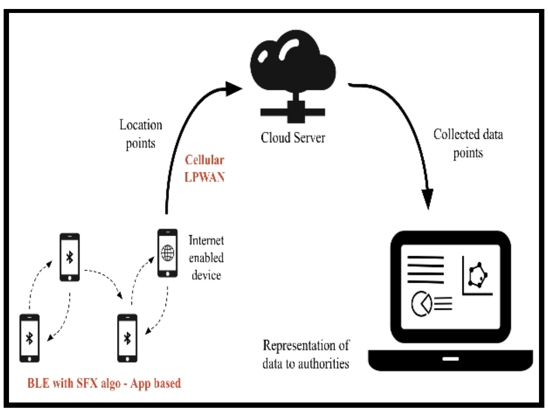

Fig 4 System Architecture Diagram

IMPLEMENTATION

Training Labels: All labels for the images are encoded into the directory structure of this dataset and extracted into a pandas Data Frames. The spatial distribution of the pictures is plotted.

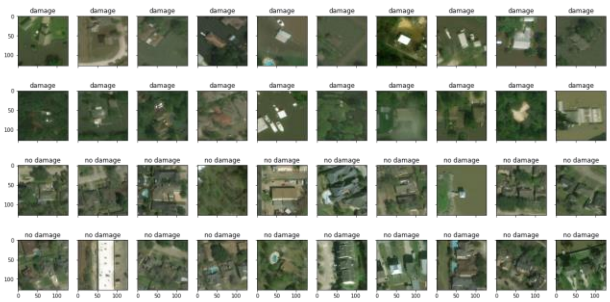

Fig 5: Spatial distribution of the images (Training Labels)

Training Images: Inspected the images and implemented RGB conversion through OpenCV Library. Below figure shows the RGB analysis of images:

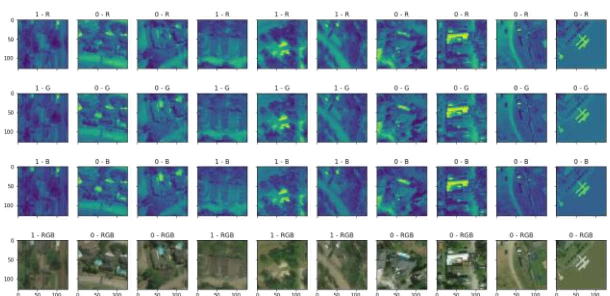

Fig 6: RGB analysis of images

Transfer Learning: In general, there are two forms of transfer learning in the context of deep learning: feature extraction and fine-tuning, however we employed the latter technique in this case. In the process of fine-tuning, we removed the fully-connected layers of an existing network, replaced them with a new set of fully-connected layers, and then fine-tuned these weights (and optionally prior layers) to detect the new object classes. When the training dataset is big and extremely close to the original dataset on which the pre-trained model was trained, this method is typically preferred.

Image Pre processing: The images were transformed into arrays so that the pre processing could be accomplished. The tf. data API allows to create huge input pipelines using reusable components. A pipeline for training an image model, for instance, might collect data from files in a distributed file system, apply random perturbations to each image, and then combine randomly selected photos into a batch for training. Instead of storing all the pictures in RAM continuously, this API allows the user to just call the data (and apply transformations, etc.) when the data is truly needed. Histogram of RGB value of image is shown below:

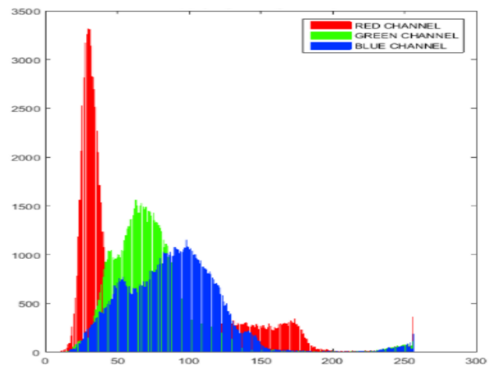

Fig 7: Histogram of RGB value

Model VGG16 model is implemented for the required results. Snapshot of our model summary is given below:

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Functional)           (None, 4, 4, 512)         14714688
_________________________________________________________________
global_average_pooling2d (Gl (None, 512)               0
_________________________________________________________________
dense (Dense)                (None, 1)                 513
=================================================================
Total params: 14,715,201
Trainable params: 513
Non-trainable params: 14,714,688
```

Fig 8: Model Summary

A sequential approach is suited for a simple stack of layers with one input tensor and one output tensor for each layer. In Keras, the simplest technique to build a model is sequential. It allows you to layer-by-layer construct a model. Each layer has weights that match the weights of the one above it.

The VGG-16 is a 16-layer deep convolutional neural network. You can load a pre-trained version of the network from the ImageNet database, which has been trained on over a million photos.

Snapshot of the VGG16 model implemented is shown in fig. 3.4. The user will be interacting through our android app. The app will be broadcasting the location of the user at a fixed interval. Users can also set the frequency of fetching the location to save the battery of the device. The app will always look for any internet connectivity to sync the data with the authorities. Users will be able to chat with the nearby users too on the scatternet network. We are using the insecure RFCOMM so that users can interact without pairing with the devices.

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 128, 128, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 128, 128, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 128, 128, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 64, 64, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 64, 64, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 64, 64, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 32, 32, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 32, 32, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 32, 32, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 32, 32, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 16, 16, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 16, 16, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 16, 16, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 16, 16, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 8, 8, 512)         0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 8, 8, 512)         2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 8, 8, 512)         2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 8, 8, 512)         2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 4, 4, 512)         0
=================================================================
Total params: 14,714,688
Trainable params: 0
Non-trainable params: 14,714,688
```

Fig.4.6: VGG16 Model

Network arrangement:

Bluetooth network arrangements (topology) can be either point-to-point or point-to-multipoint. Any unit in a piconet can establish a connection to another piconet to form a scatternet. See figure 4.4, which diagrams a scatternet in which piconet A, which consists of four units, is connected to piconet B, consisting of two units. Note that the master unit of A is not the link Bluetooth network arrangements (topology) can between the two piconets.

RESULTS

Evaluation on ten epochs is done and a considerable difference in the validation accuracy was noted. Before fine tuning, maximum validation accuracy obtained was 74.79%. On the contrary, maximum validation accuracy of 91.98% was obtained after fine tuning.

Before Fine Tuning:

```
Epoch 1/4
275/275 [==============================] - 1607s 6s/step - loss: 0.6891 - accuracy: 0.6044 - val_loss: 0.6470 - val_accuracy: 0.5667
Epoch 2/4
275/275 [==============================] - 1587s 6s/step - loss: 0.6074 - accuracy: 0.5279 - val_loss: 0.6002 - val_accuracy: 0.6062
Epoch 3/4
275/275 [==============================] - 1581s 6s/step - loss: 0.5669 - accuracy: 0.6466 - val_loss: 0.5637 - val_accuracy: 0.7042
Epoch 4/4
275/275 [==============================] - 1584s 6s/step - loss: 0.5318 - accuracy: 0.7350 - val_loss: 0.5304 - val_accuracy: 0.7479
```

Fig 9: Results before fine tuning

After Fine Tuning:

```
Epoch 5/10
275/275 [==============================] - 1918s 7s/step - loss: 0.2260 - accuracy: 0.9096 - val_loss: 0.2683 - val_accuracy: 0.8781
Epoch 6/10
275/275 [==============================] - 1930s 7s/step - loss: 0.1824 - accuracy: 0.9318 - val_loss: 0.2684 - val_accuracy: 0.9052
Epoch 7/10
275/275 [==============================] - 1923s 7s/step - loss: 0.1535 - accuracy: 0.9440 - val_loss: 0.1943 - val_accuracy: 0.9271
Epoch 8/10
275/275 [==============================] - 1927s 7s/step - loss: 0.1341 - accuracy: 0.9517 - val_loss: 0.2169 - val_accuracy: 0.9115
Epoch 9/10
275/275 [==============================] - 1934s 7s/step - loss: 0.1202 - accuracy: 0.9554 - val_loss: 0.2135 - val_accuracy: 0.9219
Epoch 10/10
275/275 [==============================] - 1926s 7s/step - loss: 0.1086 - accuracy: 0.9608 - val_loss: 0.2404 - val_accuracy: 0.9198
```

Fig 10: Results after fine tuning

After implementing the model, accuracy of 94.3% is obtained.

The user will be interacting through our android app. The app will be broadcasting the location of the user at a fixed interval. Users can also set the frequency of fetching the location to save the battery of the device. The app will always look for any internet connectivity to sync the data with the authorities. Users will be able to chat with the nearby users too on the scatternet network. We are using the insecure RFCOMM so that users can interact without pairing with the devices.

Working of Bluetooth

The innovation of Bluetooth is based on a 9mm x 9mm CPU, which capacities as a minimal expense and short-range radio connection. Bluetooth technology creates a 32-foot personal bubble and allows for simultaneous voice and data transmission between several devices. At most 8 devices can be connected in a piconet, and at max 10 piconets can exist within the 32 feet bubble. Each piconet supports up to 3 parallel full-duplex voice devices.

Types and rates of transmission:

Circuit and packet-switching are combined in the baseband protocol. To assure that packets do not arrive out of order, slots (at most five) can be reserved for synchronous packets. As noted earlier, another hop signal is used for each packet. Circuit switching can be either asynchronous or synchronous.

Network arrangement:

Bluetooth network arrangements (topology) can be either point-to-point or point-to-multipoint. Any unit in a piconet can establish a connection to another piconet to form a scatternet. See figure 4.4, which diagrams a scatternet in which piconet A, which consists of four units, is connected to piconet B, consisting of two units. Note that the master unit of A is not the link Bluetooth network arrangements (topology) can between the two piconets.

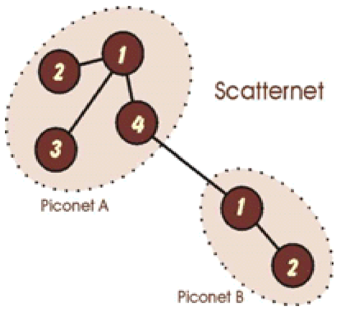

Fig 11: Scatternet and Piconet [SOURCE: packtpub.com]

Radiofrequency and spectrum hopping:
The Bluetooth radio chip operates in the unlicensed Industry Scientific Medical band at 2.4 GHz. Having started with 2.402 and finishing with 2.480, it split the GHz Frequency range into 79 hops, each one MHz apart.

Data-transmission:

Both synchronous and asynchronous data transmission is possible. Asynchronous Connectionless (ACL) is primarily used for data, while Synchronous Connection-Oriented (SCO) is primarily used for voice. Each master-slave pair in a piconet can use a various transmission method, and methods can be changed at any time.

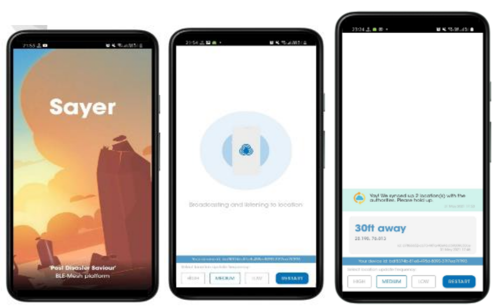

Fig 12: Sayer's app screenshots

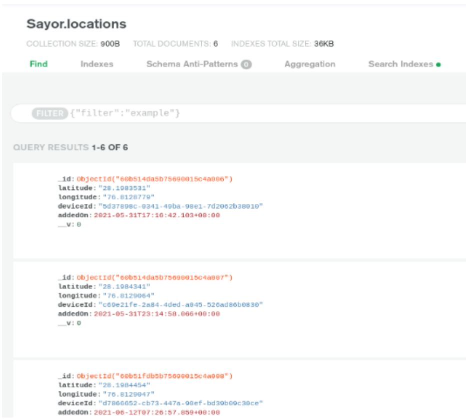

Fig 13: Sayer's DB Screenshot

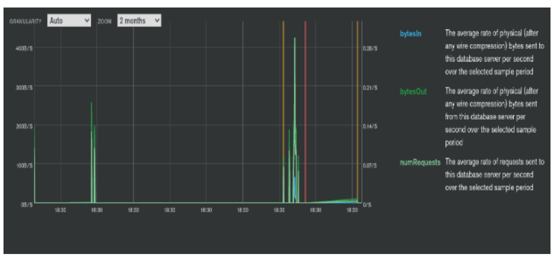

Fig 14: Database Analysis

Geometry Algorithm Implementation

Andrew's monotone convex hull algorithm forms a circular core of a set of 2 points during O (nlogn) Complexity. It does this by first arranging points lexicographically (first with x-coordinate, and in the case of a tire, with y-coordinate), and then forming the upper and lower points of the point at O(n) time. The Geometry above is part of a convex geometry, which can be seen above. It runs from its right end to the left end in a clockwise direction. The lower deck is the rest of the convex hull.

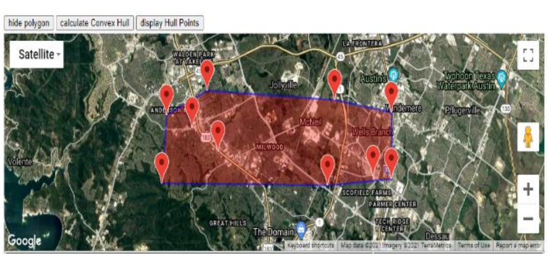

Fig 15:Working of the Map Plotting Algorithm

Performance Evaluation

For evaluating the performance of the model, by using the confusion_matrix function a confusion-matrix is obtained after importing f1_score from "scikit learn" library. With the help of the confusion matrix, Positive and negative recall, as well as positive and negative precision, were calculated. Calculation of all the above mentioned metrics is based on the following formulae.

Confusion-Matrix = [[True Positives (TP), False Negatives(FN)],[False Positives(FP), True Negatives(TN)]] ………………(1)

Accuracy = (TP+TN) / (TP+TN+FP+FN) ……...(2)
Positive-Recall = TP / (TP+FN) ……..(3)
Negative-Recall = TN / (TN+FP) ……..(4)
Positive-Precision = TP / (TP+FP) ……..(5)
Negative-Precision = TN / (TN+FN) ……..(6)

```
array([[ 895,  105],
       [  26, 1276]])
```

Fig 16: Confusion Matrix

```
accuracy = 94.3093 %
positive recall = 0.9800
negative recall = 0.8950
positive precision = 0.9240
negative precision = 0.9718
```

Fig 17: Performance Results

Two line charts are plotted, one for accuracy and the other for loss, with respect to the number of epochs

Before fine tuning:

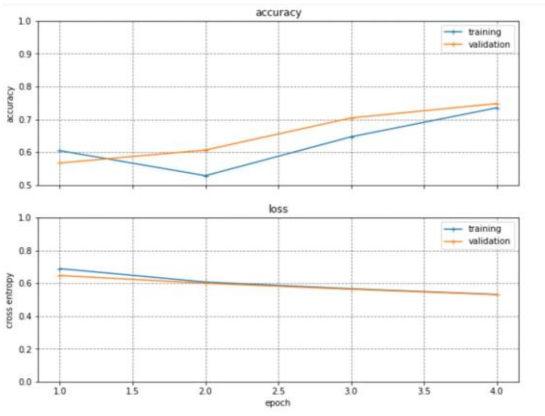

Fig 18: Performance Analysis before fine tuning

After fine tuning:

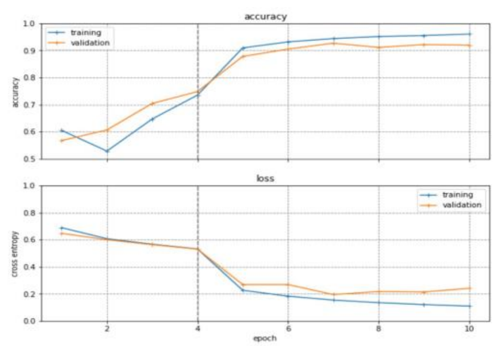

Fig 19: Performance Analysis after fine tuning

And because of using Bluetooth technology, this application is consuming very little power compared to the one which is using Wi-Fi as their source of connecting the devices. The range of the Bluetooth can be extended by using devices like Bluetooth extenders or Bluetooth repeaters. As shown in Figure 5.1, Bluetooth is about 30% more energy-efficient than Wi-Fi and perform occupancy data transmission, which means, the mobile phone has 16-17 hours of battery life when running on BLE communication scheme and 14-15 hours in Wi-Fi communication.

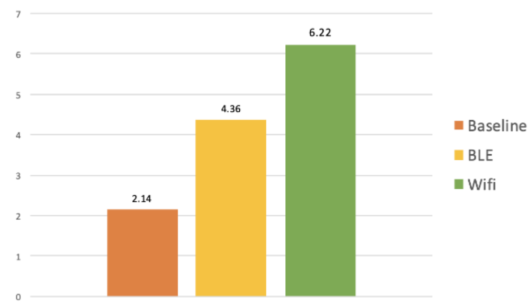

Fig 20: The average of both BLE and Wi-Fi energy consumption, as well as baseline energy usage as a comparison [Source: semanticscholar.org]

CONCLUSION & FUTURE SCOPE

Validation accuracy of 94.3% and test accuracy of 93.89% is obtained after fine tuning. By gathering more data, the model can be refined and applied to other future hurricane events. More data allows for the development of more robust models and sets of hyper-parameters. Moreover, the improvements are to be brought about by improved initial analysis with incorporation of enhanced observational databases and better first guesses from the outputs of higher resolution global models.

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The perks of using Bluetooth is that the power consumption is reduced to a great level, while the other methods are using Wi-Fi, which is more power consumption compared to Bluetooth. Another advantage of using Bluetooth is that Bluetooth is present in most devices, but the presence of Wi-Fi in non-smartphone devices cannot be assured.

Collecting and sharing emergency information and supporting the first person with internet connectivity with an IoT connector is one of the most feasible and affordable ways to keep Internet connectivity up during a disaster. UAVs (Gupta, Chauhan and Chadha, 2020) can also provide good option for managing disaster by delivering eatable and medicines to the survivors in remote locations.

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