International Journal of Engineering Technology and ManagementSciences

Website: ijetms.in Issue: 3 Volume No.6 May – 2022
DOI:10.46647/ijetms.2022.v06i03.011 ISSN: 2581-4621

Detection of Hurricane through Satellite Images

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***Abstract*— Hurricanes are the heaviest forces in nature that causes huge destruction in the ecosystem by producing strong winds and floods also called tropical cyclones. These cyclones lead to the loss of lives, destroy nature, and damage infrastructure and property. Many measures are taken to help victims of the disaster and reduce the damage caused by the disaster. But a difficulty arose to analyze the vast data that is released on social media. Satellite imagery is used for the detection of such damages due to its ability to cover large local and temporary locations. But the actual manual detection is wrong and not accurate. This paper covers the use of Machine Learning techniques to determine the place that can be affected by a hurricane. We use a dataset to predict a hurricane. In the existing system, they use algorithms such as Resent, Linear & logistic regression, and CNN. In this paper, we use the availability and readiness of satellite imagery to improve the efficiency and accuracy of detection by image separation algorithms. Satellite imagery to predict whether a particular area will be affected by the hurricane or not. Algorithms like SVM, Naive Bayes classifier, and polynomial regression are used for better performance and higher accuracy. And the pre-trained model, Alexnet method for training the data.**

***Keywords*—Hurricane, Alexnet, Machine Learning, Satellite images, Datasets.**

INTRODUCTION

Earth is a unique planet with a wide variety of living and nonliving things. Severe weather conditions like hurricanes result in greater damage to the environment. Hurricanes had a profound effect on many countries around the world. When a hurricane occurs it comes with strong winds and heavy floods thereby affecting the plants, animals, and people. They cover all the world and made vast damage to all the people and the environment. So it's the responsibility of the government to offer warnings about the present and future disasters of the Earth [1]. Predicting such catastrophes has become a prerequisite for improving the survival of all living and nonliving things. Such predictions are possible with machine learning technology. Using ML algorithms, we can analyze previous hurricane locations and predict potential future locations[2]. It helps prevent infrastructure damage and loss of lives scientists in weather forecast services use satellite images to predict the information for the future[3]. The proposed work is based on the analysis of satellite imagery as the primary data source. The added advantage of satellite imagery compared to other data is its higher spatial resolution[4]. These pictures can provide information in the event of any emergency and disaster such as hurricane damage from small to large areas around the world. Satellite images contain all the information of weather such as before and after disaster images[5].The goal is to create a model that can automatically detect that a given region may be affected by a hurricane. Helps to prevent infrastructure damage and loss of life. This results in saving the lives of humans, animals, plants, and livestock.

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Fig-1. SATELLITE IMAGE OF HURRICANE

I. LITERATURE SURVEY

The previous work was done on the various disasters such as earthquakes, floods, wildfire and hurricanes and the damage caused during the disasters.

RadhikaSudha,, Yukio Tamura, Masahiro Matsui done their work on the percentage of the damaged area of each damaged building ,which is also calculated by a newly introduced texture-wavelet analysis on roof-tops, and the results are validated by counting the damage pixels manually and results are not accurate[1].

In DiogoDuarte,FrancescoNex, Norman Kerle,GeorgeVosselman, paper, a CNN framework using residual connections and dilated convolutions is used considering both manned and unmanned aerial image samples to perform the satellite image classification of building damages. Three network configurations, trained with multi-resolution image samples are compared against two benchmark networks where only satellite image samples are used[3].

Pi, Y., Nath, N.D. and Behzadans research introduces and evaluates a series of convolutional neural network (CNN) models for ground object detection from aerial views of disaster's aftermath. Eight CNN models based on You-Only-Look-Once (YOLO) algorithm are trained by transfer learning, i.e., pre-trained on the COCO/VOC dataset and re-trained on Volan2018 dataset, and achieve 80.69% mAP for high altitude (helicopter footage) and 74.48% for low altitude (drone footage), respectively. This paper also presents a thorough investigation of the effect of camera altitude, data balance, and pre-trained weights on model performance, and finds that models trained and tested on videos taken from similar altitude outperform those trained and tested on videos taken from different altitudes[5].

Berne A. Williams and David G. Long developed a hurricane model which provides prior information that can be used in maximum a posterior probability estimation of rain-contaminated ocean winds and some useful hurricane parameters like location of eye center using sea winds instrument[13].

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II. EXISTING SYSTEM

In Machine learning, various types of CNN models like VGG, ResNet depending upon the number of convolutional layers are mainly used for finding the damage caused to the places.. In the Existing System, the detection of hurricanes is given with an accuracy level of 70-80% while They used algorithms like ResNet, CNN, Linear, and Logistic Regressions. Although Resnet has proven powerful in many applications, one of the major drawback is that deeper network usually requires weeks for training,making it practically infeasible in real world applications.With increased complexity of Resnet architecture and duration of network we propose Alexnet model in this paper to overcome the disadvantages.

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TABLE-1 EXISTING TECHNIQUES AND ACCURACY

Author	Dataset	Type Of Disaster	Technique Used	Accuracy
AminaAsif, Bissmillah Jan	Hursat-B1(version-05),Hurricane From Tropical Cyclone	Hurricane	Multivariate Linear Regression, Multilayer Perceptron, SVM,RVM,KNN	93%
SwapandeepKaur	Hurricane Sandy 2012	Hurricane	Convolutional Auto-Encoders	88.3%
Quoc Dung Cao, Young JumChoe	Houston Of Hurricane Harvey 2017	Flooded/ Damaged	Convolutional Neural Network by LeNet-5	97%
Ankur Singh	Hurricane Images From Damage Repository	Hurricane	CNN With Transfer Learning VGG	53.35%
BurcuAmirgan	Houston Area After Hurricane Having in 2017	Flooded	CNN, SSVM, Den set Net	97.29%
K Scott Mader	Tohoku Earthquake Tsunami	Earthquake	XGBOOT, Linear Regression	93%

III . PROPOSED SYSTEM

The goal of the proposed system is to predict hurricanes with the maximum accuracy by using SVM, Naïve Bayes, and Polynomial and Logistic Regression algorithms.In this paper, we shown how to get the best results from the above algorithms by comparing the accuracy. A dataset from Kaggle of size 20,000 is used to get satellite images. In the Alexnet approach, a pretrained Model Neural Network is used for training the dataset. And by using the above-mentioned algorithms we improved the results with good accuracy.

A.Methodology:

The Alexnet model was proposed by alexkrizevsky and his colleagues in the year of 2012 . and in the research paper it was named “image net classification with deep convolution neural network”.Alexnet consists of total eight layers and the model consists of five layers. All these layers uses a reluactivation except the output layer. To prevent this model from over fitting we have used the dropout layers. overall working with the project we came to know that relu is an activation function which

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performs the training process with the accuracy of six times. The image net dataset consists of 14 million images across the thousand of classes .

This model is implemented for the further reference. The input for this model is given as RGB images ..Alexnet has 5 convolution layers and also maxpoolinglayers. Softmax is used as a activation function in the output layer. We have used 62.3million parameters in this alexenet architecture

Fig-2.ARCHITECTURE OF ALEXNET

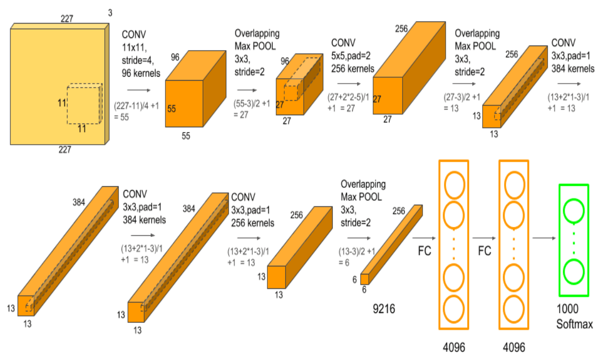

Fig-3.FLOW CHART OF ALEXNET

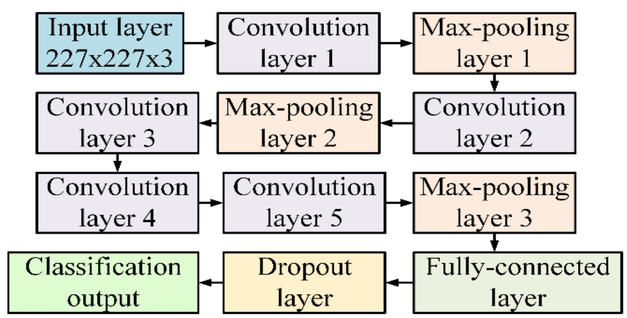

FIG-4.CLASSIFICATION OF DIFFERENT MODELS

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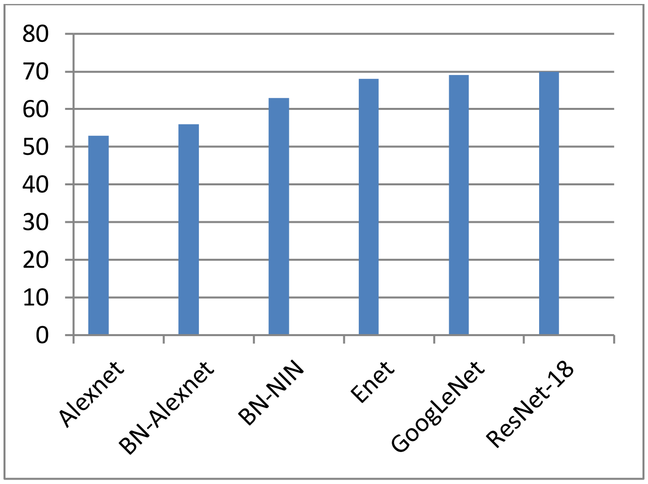
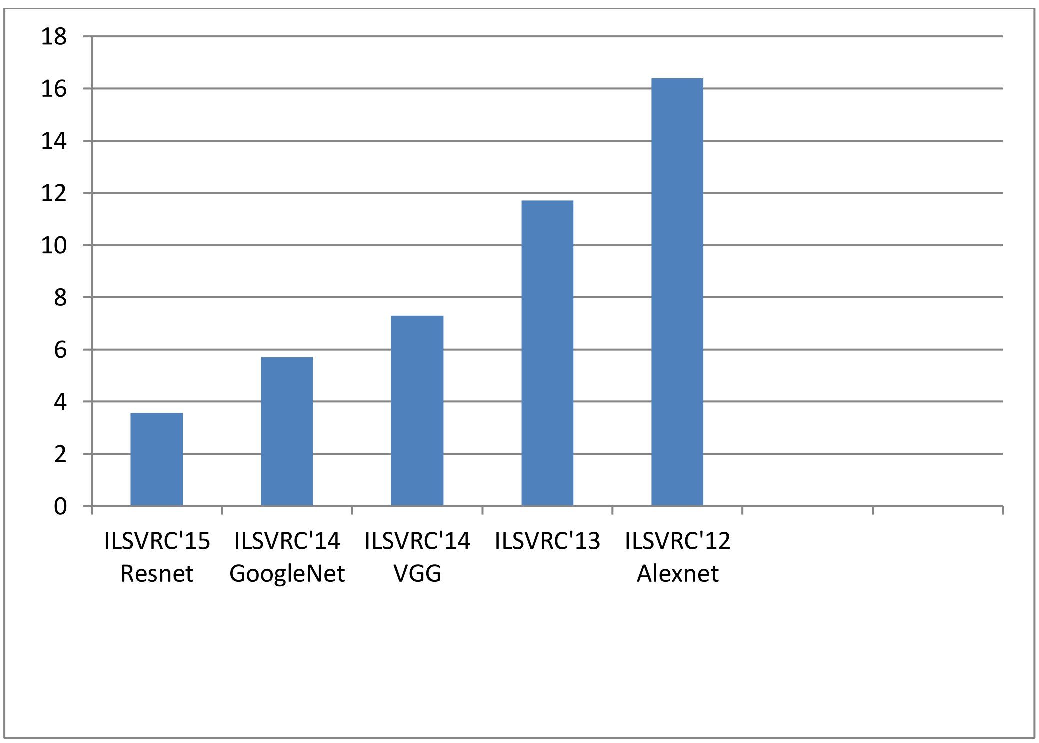


FIG-5.ACCURACY OF DIFFERENT MODELS



From the graphs Fig-4&5 it is clear that Alexnet model is best for giving high accuracy and low loss values.

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TABLE-2.SEQUENTIAL MODEL OF ALEXNET

Layer (type)	Output Shape	Param#
conv2d (Conv2D)	(None, 55, 55, 96)	34944
batch normalization	(BatchNo (None, 55, 55, 96)	384
max_pooling2d (MaxPooling2D)	(None, 27, 27, 96)	0
conv2d_1 (Conv2D)	(None, 27, 27, 256)	614656
batch_normalization_1	(Batch (None, 27, 27, 256)	1024
max_pooling2d_1	(MaxPooling2 (None, 13, 13, 256)	0
conv2d_2 (Conv2D)	(None, 13, 13, 384)	885120
batch_normalization_2	(Batch (None, 13, 13, 384)	1536
conv2d_3 (Conv2D)	(None, 13, 13, 384)	1327488
batch_normalization_3	(Batch (None, 13, 13, 384)	1536
conv2d_4 (Conv2D)	(None, 13, 13, 256)	884992
batch_normalization_4	(Batch (None, 13, 13, 256)	1024
max_pooling2d_2	(MaxPooling2 (None, 6, 6, 256)	0

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flatten (Flatten)	(None, 9216)	0
dense (Dense)	(None, 4096)	37752832
dropout (Dropout)	(None, 4096)	0
dense_1 (Dense)	(None, 4096)	16781312
dropout_1 (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 2)	8194

Total params : 58,295,042

Trainable params : 58,292,290

Non-trainable params : 2,752

The tables -3&4 shows the comparisons between Alexnet and Resnet History model with different parametric values. Comparing the loss,Accuracy,Val_loss and Val Accuracy the Alexnet model gave the best result. Therefore , Alexnet model is used in the proposed system to train the data.

TABLE-3.ALEXNET HISTORY MODEL

Epoch	**Loss**	**Accuracy**	**Val_Loss**	**Val_ Accuracy**
1/15	1.1833	0.5789	0.6091	0.6742
2/15	0.9498	0.6799	0.5438	0.7212
3/15	0.8601	0.7170	0.4926	0.7699
4/15	0.7607	0.7509	0.4667	0.8000
5/15	0.7069	0.7684	0.4477	0.8151
6/15	0.6625	0.7873	0.4097	0.8255
7/15	0.6071	0.8085	0.3903	0.8533

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8/15	0.5751	0.8099	0.3817	0.8504
9/15	0.5315	0.8292	0.3557	0.8696
10/15	0.4911	0.8428	0.3373	0.8707
11/15	0.4615	0.8528	0.3222	0.8765
12/15	0.4449	0.8591	0.3088	0.8812
13/15	0.4413	0.8561	0.2863	0.8962
14/15	0.4093	0.8660	0.2698	0.9003
15/15	0.3980	0.8728	0.2661	0.9078

TABLE-4.RESNET HISTORY MODEL

Epoch	**Loss**	**Accuracy**	**Val_Loss**	**Val_Accuracy**
1/15	1.1410	0.3678	0.5070	0.5631
2/15	0.8468	0.4757	0.3426	0.6101
3/15	0.7500	0.6060	0.3815	0.6587
4/15	0.6504	0.6408	0.3536	0.7000
5/15	0.6058	0.6573	0.3421	0.6121
6/15	0.4641	0.5741	0.3068	0.7224
7/15	0.5090	0.7064	0.2802	0.7520
8/15	0.4850	0.7009	0.2810	0.7001
9/15	0.4214	0.7250	0.2630	0.6382
10/15	0.3701	0.7416	0.4303	0.6704
11/15	0.4310	0.7526	0.2487	0.7580

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12/15	0.4081	0.7481	0.3088	0.8013
13/15	0.2413	0.7501	0.2593	0.8432
14/15	0.4093	0.8660	0.2698	0.6353
15/15	0.3080	0.7516	0.3032	0.8042

The graphs from the fig-6&7 denotes that the accuracy and loss of testing and training model that is varying with the number of epochs. The accuracy of the model increasing and the loss model decreasing. For a model to give the best result the conditions are satisfied, hence Alexnet is used to train the model.

FIG-6 ALEXNET MODEL ACCURACY

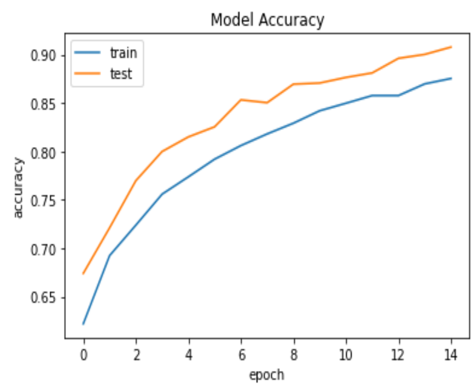
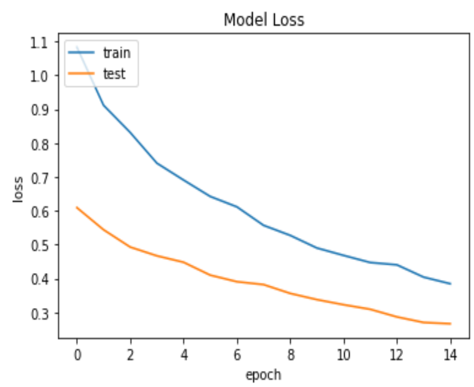


FIG-7 ALEXNET MODEL LOSS



*Confusion Matrix***:** By measuring the quality of predictions from algorithms a classification report table 5&6 is prepared for both Alexnet and Resnet model. Comparing the two reports we concluded that Alexnet is the best approach giving the best precision value upto 90%.

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FIG-8. DAMAGE & NO DAMAGE OF IMAGES

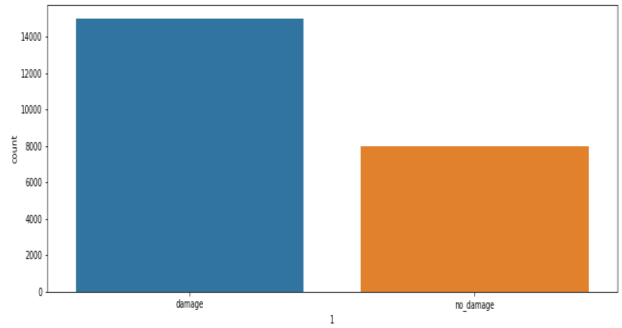

TABLE-5.CLASSIFIFCATION REPORT OF RESNET

	precision	Recall	f1-score	support
0	0.70	0.83	0.86	2618
1	0.80	0.70	0.90	1870
Accuracy	0.80	0.80	0.87	4640
Macro_avg	0.80	0.81	0.79	4640
Weighted_avg	0.80	0.78	0.90	4640

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TABLE-6.CLASSIFIFCATION REPORT OF ALEXNET

	precision	**Recall**	**f1-score**	**support**
0	0.90	0.95	0.92	3739
1	0.90	0.79	0.84	2011
Accuracy	0.90	0.86	0.90	5750
Macro_avg	0.90	0.87	0.88	5750
Weighted_avg	0.90	0.90	0.90	5750

FIG-9 CONFUSION MATRIX OF ALEXNET

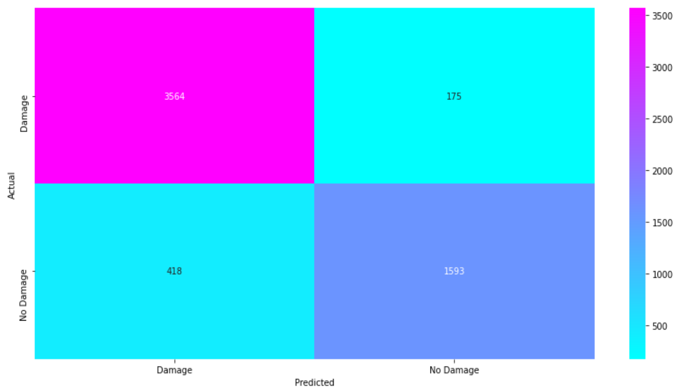

Fig -8 shows the damage and a non damage image from the dataset.Fig-9 is confusion matrix for all the actual and predicted images of Alexnet. The true positive of damage and false negative of no damage is high.

IV.IMPLEMENTATION RESULTS

A.SVM Classifier:Considering the loss values decreasing and accuracy values increasing from Table-7 ,it indicates the model is trained in a good way. So the SVM Algorithm gives an accuracy of 95%.

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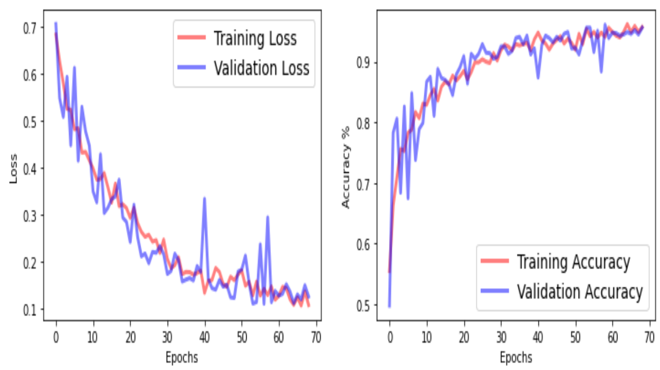
TABLE-7.SVM ALGORITHM ACCURACY REPORT

Loss	Accuracy	Val_Loss	Val_Accuracy
0.6819	0.5550	0.7045	0.4980
0.1084	0.9620	0.1120	0.9490
0.12141	0.9490	0.1302	0.9460
0.1201	0.9570	0.1260	0.9560

Fig-10.LOSS AND ACCURACY OF SVM



B.Logistic Regression: Logistic Regression Algorithm gives an accuracy of 87% from table-8

TABLE-8.SVM ALGORITHM ACCURACY REPORT

Loss	Accuracy	Val_Loss	Val_Accuracy
4.8605	0.8637	4.6375	0.8875
4.5301	0.8697	4.3305	0.8869
4.2140	0.8794	4.0336	0.8819
3.9370	0.8684	3.7436	0.8863
3.6436	0.8788	3.4750	0.8906

Fig-11.LOSS AND ACCURACY LEVELS OF LOGISTIC REGRESSION

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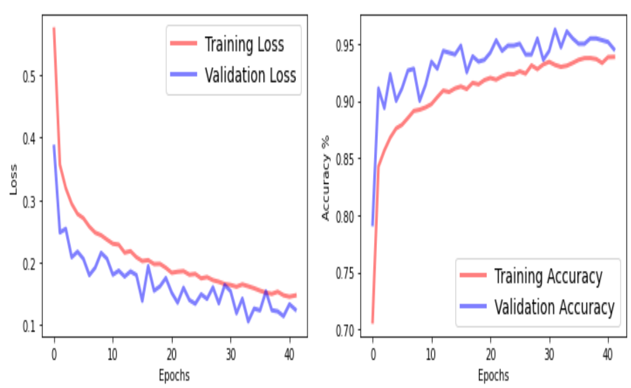
*C.Naive Bayes Classifier***:**Naive Bayes Classifier gives an accuracy of 93% from table(ix)

TABLE-9.NAIVE BAYES ACCURACY REPORT

Loss	**Accuracy**	**Val_Loss**	**Val_Accuracy**
0.1533	0.9366	0.1219	0.9547
0.1477	0.9332	0.1142	0.9531
0.1454	0.9383	0.1334	0.9516
0.1474	0.9385	0.1248	0.9453

Fig-12.LOSS AND ACCURACY OF NAÏVE BAYES



D.Polynomial Regression: Polynomial Regression Algorithm gives an accuracy of 87% from table-10.

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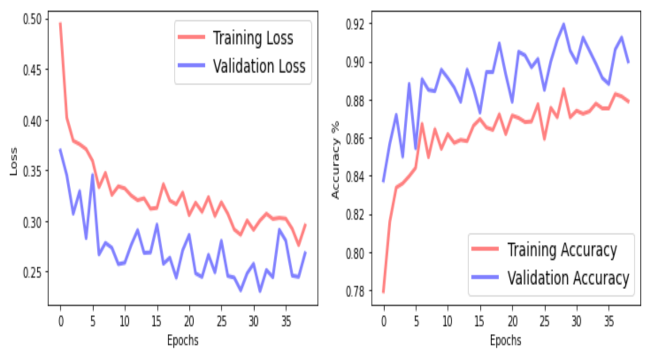
TABLE-10.ACCURACY & LOSS REPORT

Loss	Accuracy	Val_Loss	Val_Accuracy
0.3018	0.8778	0.2443	0.8988
0.3029	0.8753	0.2912	0.8913
0.3021	0.8753	0.2805	0.8881
0.2760	0.8816	0.2447	0.9125

Fig-13.LOSS AND ACCURACY OF POLYNOMIAL REGRESSION



From fig-10,11,12,13 Initially the training loss is high ,but after few epochs it decreased. And the validation Accuracy increased after few epochs. The training and validation points both decreased in loss and increased in accuracy and after sometime they stabilized at certain point. This is neither overfittimg nor under fitting .This indicates a near optimal fit .

V.CONCLUSION

In this paper, we detected the possibility of a hurricane affecting places using satellite images. We used SVM, Naïve Bayes, Logistic and Polynomial Regression algorithms and a pre-trained model Alexnet and got the accuracy level of 89-95%.Out of these algorithms SVM algorithm has given the best accuracy of 95%. And it is very fast and effective when compared to all other algorithms. This approach is helpful in disaster predictions and image classification applications.

VI.ACKNOWLEDGMENT

We would like to thank our guide Mr. V. Chandra Sekhar Reddy and project coordinator Mrs. Soppari Kavitha for their continuous support and guidance. Due to their guidance, we can complete our paper successfully. Also, we are extremely grateful to Dr.M.V. VIJAYA SARADHI, Head of the Department of Computer Science and Engineering, ACE Engineering College for his support and valuable time.

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DOI:10.46647/ijetms.2022.v06i03.011 ISSN: 2581-4621

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