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The Effects of Climate Change on Rainfall Pattern in Warri Metropolis, Nigeria.

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Abstract

The study examines rainfall characteristics in Warri metropolis for the past 30 years (1986-2015). Rainfall data was collected from the archives of Nigerian Meteorological Agency; and oral interview was also conducted. The study exploited rainfall characteristics such as daily, monthly and yearly amount of rainfall, intensity, frequency, variability, trends, return period and fluctuation of rainfall. Simple Linear Regression analysis and Standardized Rainfall Anomaly Index (SAI) were used to analyze the data. Among other findings, the correlation coefficient (-0.156) shows a negative relationship between rainfall and time (years). The trend line regression equation Y=243.75-0.4572X, confirms that rainfall in Warri Metropolis is decreasing at the rate of -0.45 per year. Recommendations given included continual monitoring and study of rainfall characteristics and other climatic data and dissemination of such information for planning purposes; drastic reduction of gas flaring in the metropolis, legislation against indiscriminate deforestation and need for proper urban planning.

Keywords: Climate Change, Rainfall, Disaster, Weather and Climate

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Introduction

The prevailing pattern of rainfall in an area influences virtually every aspects of the place as well as survival of lives therein, ranging from shelter/housing systems, transportation, agriculture, religion to socio-cultural activities. A change in the known pattern of rains will definitely present a new set of challenges to which the inhabitants are hitherto used to. The existence and reality of climate change is no longer a question of doubt, the consequences are seen and felt everywhere. Indeed the earth's climate has not been static since inception but the rapidity, frequency and severity of the consequences of climate change in the last few decades are however, alarming [1].

Afangideh, *et al.*, [2] highlighted the current and projected manifestations of climate change to include global warming (increase in temperature), rise in sea level, shifting of global climate zones, changes in the intensity, quality, duration and general pattern of rainfall leading to drought, desertification, and flooding; melting of glaciers/polar ice and increased incidences and severity of extreme weather events, among other effects. Indeed the occurrence of most natural disasters including flood is directly or indirectly attributed to the nature of weather and climate of such environment.

As an index of weather, precipitation, especially rainfall characteristics such as its amount, frequency, intensity and general patterns had witnessed different types of changes globally in the last few decades, and has continues to change. Odjugbo, P.A.O. [3] asserted that climate change has caused a shift in the normal timing and length of wet and dry seasons, shift in the seasonal variability of weather and climate; and increased seasonal fluctuation of water bodies. Some parts of the world experience no or little rainfall with low intensity and frequency; some other parts experience excessive rains with high intensity and frequency while others experience moderate rains. Each of these rainfall characteristics has far reaching implications, both positive and negative. For instance, in the aviation sector severe weather conditions such as haze, thundering, rainstorms (all which are related with rain or rainy season) often lead to cancellation and delay of flights. Early or excessive rainfall duration/amount and intensity influences flood events, while early cessation, low rainfall duration and low amount often lead to drought. There are also consequences on agricultural, health and other sectors [4].

Like most elements of weather and climate, the impacts of climate change with reference to rainfall could both be positive and negative and the Warri Metropolis is not an exception. For instance, rain provides source of water for domestic consumption, industrial use in the metropolis; rainfall characteristics (duration, intensity, thunderstorm, etc) influence the transportation system, business activities, agricultural production and health status of the residents. Different parts of the world experience different types of extreme weather events and disasters such as hurricane, heat wave, wildfire, and flood among others.

Climate Change and Rainfall Pattern

Ekwe, *et al.*, [5] Reported that the trends in the rainfall pattern over India between 1901 to 2003. The difference in mean annual rainfall over the regions of West and Central

Africa because of the severity in drought conditions was confirmed by Igweze, *et al.,* [6]. Their findings and results showed that long-term trend of rainfall series over these regions depict major climatic discontinuity. Ekpoh *et al.,* [7] considered the changing pattern of rainy days in Nigeria from 1919 to 1985, showed that the trend suggested a general decline in rainfall values in recent times. Rainfall values for the years under study suggested values between 265.37mm and 320.21mm.Rainfall characteristics in Nigeria have been studied for dominant trend notably [6]. They found that there was a progressive early decline of rainfall over the country. Following the pattern, they reported a noticeable and significant decline of rainfall frequency in September and October which coincide with the end of rainy season in almost every parts of the country especially in the Northern and Central parts [5]. As this may not be true in all parts of the country, there is vital need to update these researches even using data up to current years (preceding year) to appreciate the dynamism of climatic data. The need to monitor rainfall patterns and other characteristics due to their far-reaching implications are well established above.

Some aspects of the climate of north-western Nigeria, focusing more on rainfall, its inter- and intra-annual variability and patterns of distribution. Their study found that climatic conditions in north-western Nigeria have altered substantially as four drought episodes took place within the last three decades of the 20th Century. They asserted that the rainfall of that region has fluctuated substantially. Such fluctuations affect both inter-annual and intra-annual rainfall patterns. Fluctuations in inter-annual rainfall totals are not confined to the mean-state conditions but also affect the standard deviation and the coefficient of variation. Their study revealed the Sahel as a climatically sensitive region in which rainfall exhibits considerable variability on multiple time scales[7].

The studied rainfall seasonality in the Niger Delta region, using both monthly and annual rainfall data from 1931 to 1997 Adejuwon, J.O. [8] indicated a wet season with over 95 % of the total annual rainfall in the area. It also showed a long wet season from February/March to November and a short dry season from December to January/February. The northward part of the region was observed to have increase in rainfall, adding that the variation of rainfall in the locality could probably be as a result of rainfall determinant factors different from the inter tropical discontinuity. The Objective of this study is attempted to examine rainfall characteristics and pattern in the past 30 years and its implication on flood occurrences and other weather extremes in Warri Metropolis.

Materials and Method

Rainfall data from 1986 to 2015 were collected from the Nigeria Meteorology Agency (NIMET), Warri station. Rainfall characteristics the research exploited include daily, monthly and yearly amount of rainfall, intensity, frequency, variability, trends, return period and fluctuation of rainfall.

Coefficient of variation was used to determine the percentage deviations in rainfall values for the study period; it showed the degree of variability in the monthly and yearly means of rainfall. Five-year moving average was used to detect fluctuations of rainfall in the metropolis from the dataset collected. To calculate the intensity of rainfall, both yearly and monthly run of 30 years, the formula below was adopted after[2];

$$Intensity\ of\ rainfall = \frac{annual\ rainfall\ amount\ (mm)}{annual\ rainfall\ duration\ (days)}$$

This method of analysis, according to Ologunorisa, T.E. [9] has been used by Sharon (1979, 1981); Adelekan, (1998) and several others in the study of rainfall trends.

Simple Linear Regression Analysis

This statistical method was employed to determine the patterns/ trends of rainfall in the study area. [6] and [9] had adopted this tool in similar studies.

Standardized Rainfall Anomaly Index (SAI)

According to Ologunorisa, *et al*.,[10] this technique is very effective and most commonly used for studying variability of regional climate change studies. Hence, it was employed to assess variability of rainfall in the study area. The equation is

$$\text{SAI} = \frac{\sum(X-\overline{X})}{STD}$$

Where;
x = annual rainfall totals
$\bar{x}$ = mean of entire series
STD = standard deviation of mean of the series

Results and Discussion

Descriptive Pattern of Monthly Rainfall Amount in Warri Metropolis

Table 1 shows the monthly pattern of rainfall over the period of study. The highest monthly rainfall recorded was 14580.80 mm in the month of July, followed by 12430.00 mm in September, 11723.80 mm in August and 10344.40 mm in October. It can be concluded that rainfall was at its peak in the months of July, September, August and October in the study area. However, the lowest total of 869.80 mm occurred in the month of January, followed by December with 1037.80 mm and February with 1766.60 mm. This period can be categorized as the period of low flow over the 30 years period of study. The mean monthly rainfall recorded was also highest in the month of July (486.03 mm) and lowest in the month of January (28.99 mm).

Table 1: Results of the Analysis of Monthly Rainfall Amount (mm) 1986-2015

Months	Rainfall (mm)	Mean	STD	CV
January	869.80	28.99	33.59	115.87
February	1766.60	58.89	51.98	88.27
March	3925.70	130.86	60.09	45.93
April	6468.21	215.61	83.32	38.64
May	8753.10	291.77	95.23	32.64
June	9941.40	331.38	100.18	30.23
July	14580.80	486.03	203.54	41.88
August	11723.80	390.79	156.82	40.13
September	12430.00	414.33	137.09	33.09
October	10344.40	344.81	149.34	43.31
November	3355.60	111.85	66.53	59.48
December	1037.80	34.59	50.46	145.88

The results of the coefficient of variation in Table 1, revealed that monthly rainfall amount is highly variable in the months of January, February, November and December, in which the coefficients of variation were above 50 %. Figure 2 revealed that the month of July recorded the highest mean monthly rainfall in the study area; followed by the months of September, August, October and June, marking the peak of rainy season in the metropolis. While the months of December, January and February recorded the lowest mean monthly rainfall for the 30 years of study, marking the limit of dry season in the area. The area generally experiences a single peak of rainfall in July.

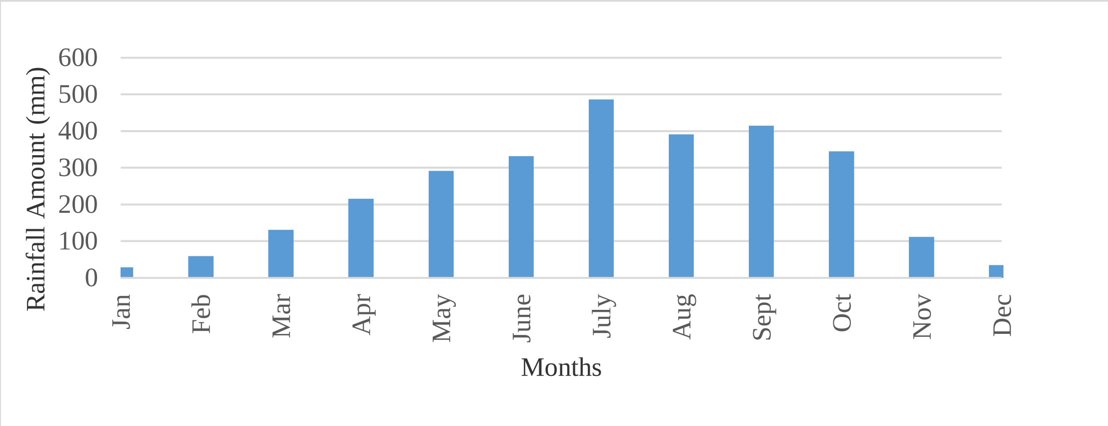

Figure 1: Mean Monthly Rainfall in Warri, 1986-2015

Pattern of Annual Rainfall Amount

Figure 1 shows the descriptive pattern of annual amount of rainfall received in the study area for the period of 30 years (1986-2015). It revealed that the year 1995 recorded the highest annual total 3437.80 mm with a mean of 268.48mm rainfall amount. Other years with high annual mean rainfall include 2002 (276.48 mm), 1997 (273.11), 1992 (267.18 mm), 2015 (265.31 mm), 1990 (265.06 mm), 2008 (263.83 mm), 1999 (261.79 mm), 2004 (255.67 mm), 2014 (245.60 mm). While the year 2009 on the other hand recorded the least annual total of 2296.40 mm with the mean of 191.37 mm rainfall amount. It is followed by 2005 (197.38 mm), 2001 (199.22 mm), 2003 (202.74 mm) and 1998 (207.73 mm) respectively. The rainfall fluctuation pattern recorded on yearly basis in the area can be said to be a function of the migration pattern of the Inter Tropical Discontinuity (ITD) over the study area. The ITD is the rainfall producing system in Nigeria.

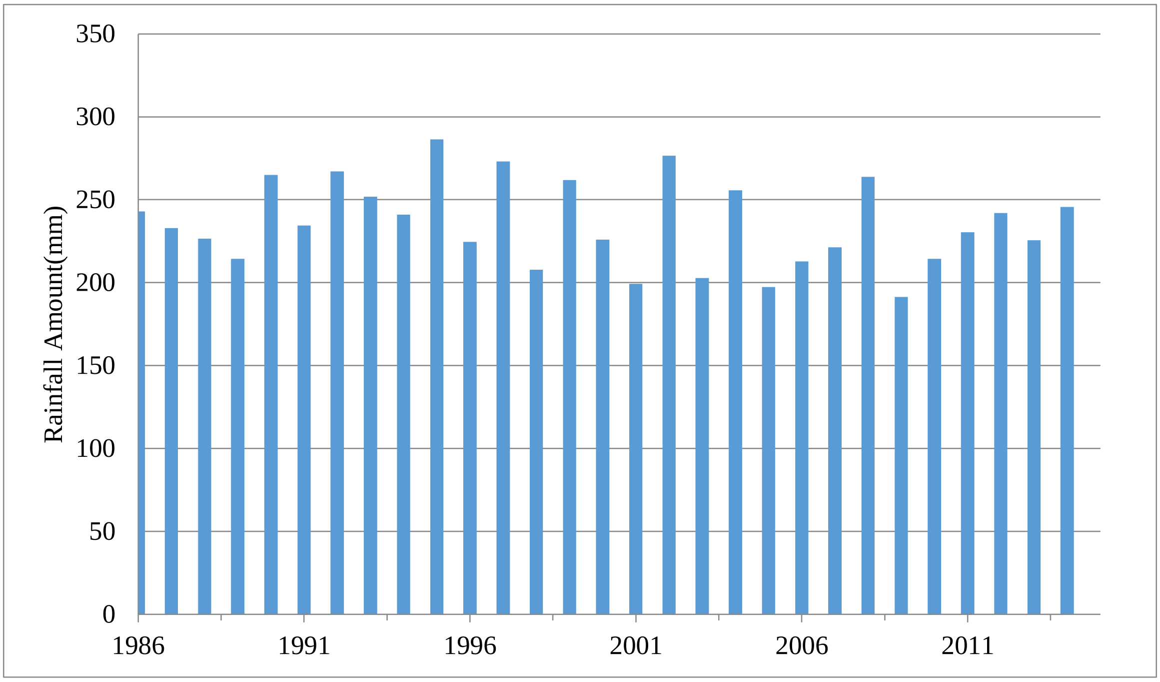

Figure 2: Mean Annual Rainfall (mm) in Warri, 1986-2015

Trend/Pattern of Rainfall in Warri Metropolis

The trend in rainfall amount over time was determined using regression analysis and the result is displayed in table 2. The p-value for the rainfall slope of 0.412 obtained is greater than 0.05, hence, there is no statistically significant relationship between rainfall and year at 95 % confidence level for the 30 years period of study. The R-squared statistic shows that the model, as fitted, explains 2.40 % variability in rainfall in the study area. The correlation coefficient of -0.156 reveals a negative relationship between the rainfall and time (year). This suggests that rainfall is decreasing over time in the study area. Since the decreasing trend observed is not statistically significant (that is, the trend is random), decrease in the future cannot be categorically predicted or ascertained and the trend cannot be attributed to a particular causative factor in the study area.

Table 2: Trend/Pattern of Rainfall Derived from Regression Analysis

Variables	Regression Equation	P-value	Statistically Significant	Sample Correlation	R^2
Warri	Y=243.75-0.4572X	0.412	No	-0.156	02.4%

The graph (Figure 2) obtained from the plot of annual rainfall amount against time has a negative trend line and revealed that annual rainfall amount is on the decrease in the last three decades in the study area. From the trend line equation, it can be concluded that the rainfall amount is decreasing at a rate of -0.45mm per year during the 30 years period under consideration.

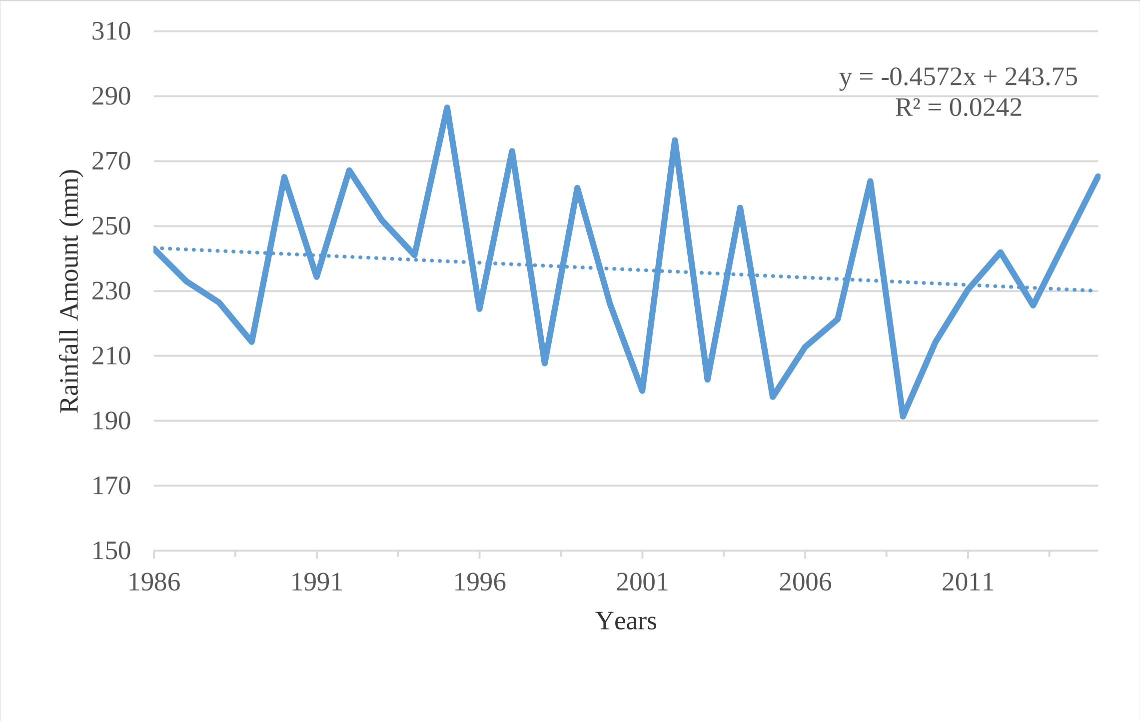

Figure 3: Rainfall Trend Pattern in Warri (1986-2015)

Figure 3 or 4 shows the annual rainfall and five year moving average curve for Warri Metropolis from 1986–2015. The five year moving average curve shows declining trend from 1986 to 1989; increasing trend from 1990 to 1997; declining trend from 1997 to 1999, but the curve start increasing again from 1999 and peaked at 2002. However, the curve starts declining again till 2013, although with variation in the level of declining, before it peaked again in 2015.

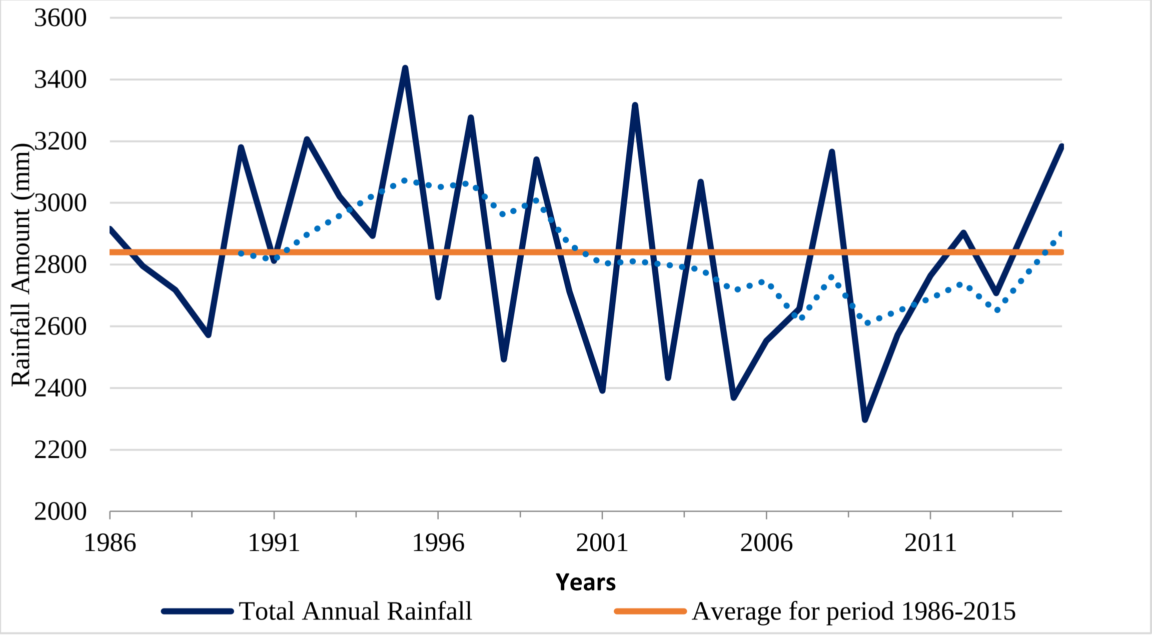

Figure 4: Rainfall Fluctuation with 5 Years Moving Average in Warri, 1968-2015

Standardize Rainfall Anomalies Index (SAI) was used to establish the dry and wet episodes in the study area for the period of study and the results are presented in Table 3. For critical analysis the thirty years under consideration were divided into three periods of ten years (decade) and the number of dry and wet episodes (years) within these ten years period were identified. The results revealed great insight into the nature of rainfall vis-à-vis the seasons (rain and dry) in Warri Metropolis for the past three decades.

Table 3: Dry and Wet Episodes in Warri in the last Three Decades (1986–2015)

Periods (Decades)	**Dry Years**	**Wet Years**
1986-1995	1987 (-*0.14*), 1988 (-*0.39*), 1989 (-*0.86*), 1991 (-*0.09*)	1986 (*0.24*), 1990 (*1.10*), 1992 (*1.18*), 1993 (*0.58*), 1994 (*0.17*), 1995 (*1.93*)
1996-2005	1996 (-*0.47*), 1998 (-*1.12*), 2000 (-*0.41*), 2001 (-*1.45*), 2003 (-1.31), 2005 (-*1.52*)	1997 (*1.41*), 1999 (*0.97*), 2002 (*1.54*), 2004 (*0.73*)
2006-2015	2006 (-*0.92*), 2007 (-*0.59*), 2009 (-*1.75*), 2010 (-*0.86*), 2011 (-*0.24*), 2013 *(-0.43*)	2008 (*1.05*), 2012 (*0.20*), 2014 (*0.35*), 2015 (*1.10*)

**Standard Rainfall Anomalies Indices are italicized in parentheses.

On the whole, there were 16 dry years out of the thirty years period considered in this study. Table further revealed an average of six dry years in every ten years in the last twenty years in the study area. Figure 5 revealed the pattern of rainfall anomalies in the study area for the thirty years period with the sixteen dry years and fourteen wet years on the negative and positive sides of the graph, respectively.

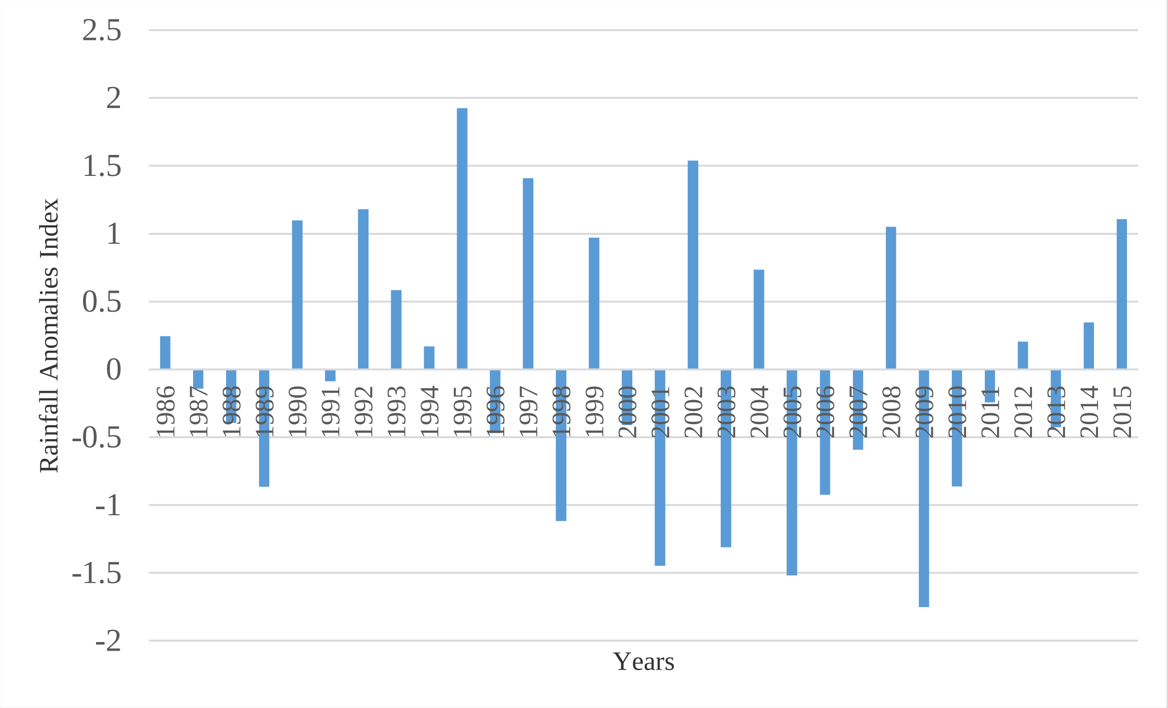

Figure 5: Pattern of Rainfall Anomalies in Warri, 1986-2015

The study revealed that the maximum total monthly rainfall for the study years occurred in July (14580.80 mm) while the minimum was recorded in January (869.80 mm). The maximum annual total rainfall and maximum annual mean rainfall was recorded in 1995 with 3437.80 mm/d and 268.48 mm respectively, while the year 2009 received the least annual rainfall total (2296.40 mm) and mean (191.37 mm).

Trend analysis revealed the R^2 statistics of 02.4, and this is able to explain about 2.40 % of rainfall variability in the metropolis. The correlation coefficient shows -0.156 which indicates a negative relationship between rainfall and time (years). This means that rainfall is decreasing over time in Warri metropolis. From the trend line regression equation Y=243.75-0.4572X, it can be concluded that rainfall in Warri Metropolis is decreasing at the rate of -0.45 per year. However, the p-value 0.412 is greater than 0.05, hence, the trend is not statistically significant at 95 % level of confidence, that is, the trend is random. By implication, future decrease in rainfall amount in subsequent years in the metropolis cannot be assured.

Conclusion, Recommendations and Planning Implication

The rainfall situation in the area as well as other climatic variables should be continually studied and monitored since they have major effects on flood occurrence and frequency, and such information should be made readily available to the urban planners, road engineers and other concerned professional and individual alike in the metropolis for effective planning purposes.

As a matter of urgency the Federal Government of Nigeria should make concrete efforts at stopping or at least reducing gas flaring in the Niger Delta, not just passing legislations that are hardly enforced. As obtained in developed nations, the oil multi-national companies should stop the unprecedented flaring of gas in the oil-rich Niger Delta.

The Delta State environmental laws should be reviewed and updated and check to see if there is a legislation against indiscriminate deforestation, bush burning, uncontrolled grazing, etc, because these anthropogenic activities have implications on the climate of the metropolis.

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Speech Emotion Classification Analysis using Short-term Features

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Abstract

Speech is an auditory signal produced from the human speech production system used to express ourselves. In this era, speech signals are also used in biometric identification technologies and interacting with machines, so that it can give different response. Emotion recognition is not a new topic and researches and applications exist using different methods to extract specific features from the speech signals. This paper presents a classification analysis of emotional human speech only with short term processing features of the speech signals using artificial neural network based approach. Speech rate, pitch and energy are the most basic features of speech signal but they still have significant differences between emotions such as angry and sad. The most common way to analyze the speech emotion is to extract important features which are related to different emotion states from the voice signal. In the speech pre-processing phase, the samples of four basic types of emotional speeches sad, angry, happy, and neutral are used. Then feed those extracted short term features into the input end of the classifier and obtained different emotions at the output end. 23 short term audio signal features of 40 samples of two frames are selected and extracted from the speech signals to analyze the human emotions. These derived data along with their related emotion target matrix are fed to test and design the classifier using artificial neural network pattern recognition algorithm. The confusion matrix is generated to analyze the performance results. The overall correctly classified results for two times trained network is 73.8 %, while increasing the training times to ten, 95 % of the emotions are correctly classified. The accuracy of the neural network system is improved by multiple times of training. The overall system provides a reliable performance and correctly classifies more than 85 % for the new non-trained dataset.

Keywords: Confusion Matrix, Neural Network, Short-term Features, Speech Emotions

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Introduction

In human interaction, emotions play important role. Human beings possess and express emotions in everyday interactions with others. When we talk about communication, it is striking that *what* we are talking, but it is more consequential that *how* we are expressing. There may be different types of sign that indicate emotions. In communication between human–human, emotions can be expressed in terms of verbal or facial. Speech signals contain different types of information including not only the information about message but also speaker's identification, emotions identification and identification of language and so on.

One important aspect of human-computer interaction is to train the system to understand human emotions through voice. People can use their voice to order commands to many electrical devices such as car, smart phone, computer, etc. Hence make the devices understand human emotions and give a better experience of interaction. Typically, the most common way to recognize speech emotion is to first extract important features that are related to different emotion states from the voice signal (e.g.: energy is an important feature to distinguish happy and sad), then feed those features to the input end of a classifier and obtain different emotions at the output end.

Speech analysis can be done either in time domain or in frequency domain using the short term or mid-term processing of speech. Short-term processing features divide the speech signals into short analysis segments which are isolated and processed with fixed properties. Mid-term processing features divide the audio signal into mid-term segments and which are used to compute the statistical values. The important problems in this emotion classification analysis is only using the short term features of the speech signals and analyze the performance of the neural network classifier.

Review of previous work

There have been many studies about speech recognition in recent years, different features as well as different classification methods have been used, i.e. Nogueiras *et al*., used Hidden Markov Models (HMM) to recognize emotions from the features pitch and energy where the accuracy is 80 % [1]. B. Schuller *et al*., used four different classification methods to compare their performance and to recognizing emotions [2] using HMM [3, 4], Naive Bayes Classifier [5], and Decision Tree Classifier [6]. Alexandros Georgogiannis, Vassilis Digalakis introduced one of speech's features *Teager MFCC*, which can also work in noisy environment [7]. Singh *et al*., described database development for Hindi Hybrid word and main focus is to analyze database using end point detection [8]. Mina *et. al*. reported an effort towards automatic recognition of emotional states from continuous Persian speech by building database of emotional speech in Persian. The resulting average accuracy was about 78 % [9]. Valery A. Petrushin described an experimental study on emotion recognition by developing 140 utterances per emotional state. Each utterance was recorded using close talk microphone. Vocal energy, frequency, formats were used for feature extraction using neural network. He presented result with accuracy of 61.4 % for happiness, 72.2 % for anger, 68.3 % for normal [10].

Speech signals are produced from a time varying vocal tract system with time varying excitation. Due to this reason, the speech signals are non-stationary in nature but, in blocks of short time speech signals are viewed as a stationary [11]. Spectral and prosodic features are used for speech emotion recognition because both of these features contain the emotional information. Fundamental frequency, loudness, pitch and speech intensity and glottal parameters are the prosodic features used to model the different emotions. The Mel-Frequency Cepstrum Coefficients (MFCC) is an accurate representation of short time power spectrum of a sound [12]. The audio signals are broken into possibly overlapping frames and a set of features is computed per frame. These short analysis segments are called analysis frames and overlap in one another [13].

Materials And Methods

To this classification, samples of recorded English speech signals of four emotions are used from the Emotional Prosody speech and Transcripts in the Linguistic Data Consortium (LDC) Dataset, in which actors and actresses perform different emotions. The speech samples for four emotions categories in the dataset contain both male and female speakers. Samples are taken from the speech and the analog signals are converted to digital signals. Each speech sentence is normalized to ensure that all the sentences are in the same volume range. At the last process uses the segmentation to separate the signal into frames so that the speech signal can maintain its characteristics in short duration. Each sample is between one second in length and separates each sample into two overlapping frames with 30 ms segments. Usually the speech signal properties change slowly with time, hence allowing the examination of short time window of speech to extract parameters. In general, the time-domain short-term audio features are extracted directly from the samples of the audio signal. Typical examples of the short-term features are the short-term energy, short-term Zero-Crossing Rate (ZCR), short-term entropy of energy, short-term harmony, Mel-Frequency Cepstrum Coefficients (MFCC), Spectral entropy, Spectral flux, Spectral entropy, Spectral centroid and the spectral spread [14].

These features are extracted from the speech signals to create and load input data and target data. A 23×80 matrix is used to create input data which indicates 23 features of 40 samples of two frames. Here, 13 short-term feature values for MFCC, two feature values for spectral centroid and one different value for each of the other eight features are extracted from the audio signals and the values are stored in a vector as an input data. Target data is 4×80 matrix which indicates the four emotion states for these 40 samples of two frames. After importing those data, next step is to randomly divide the percentage of input data into three categories namely training, validation and testing. The training set is used to fit the parameters of the classifier i.e., to find the optimal weights for each of the features. The validation set is used to tune the parameters of a classifier that is to determine a stop point for training set. Finally, the test set is used to test the final model and estimate the error rate.

The input vectors and target vectors are randomly divided into three data sets as follows:

(i) 70 % is used for training.

(ii) 15 % is used for validation to measure network generalization, and to halt training when generalization stops improving.

(iii) The last 15 % is used for testing and it has no effect on training and provides an independent measure of network performance during and after training.

A total of 80 sample data have been split by 56 of which are used in the training session, the 12 for the validation and 12 for the testing. The training, validation and test data sets are mutually exclusive in each run.

The back propagation neural network model is selected to classify the emotions since it is the most significantly used model for emotion classification and back propagation is better than the other neural network models. We can infer that when handling noise and multiple inputs of data, back propagation performs better than the pattern recognition method SOM. Another method called LVQ is an excellent for classification, but when handling noise, it is a little bit worse than back propagation method [15]. Finally, train the system to classify the emotions according to the input and target matrices. Let the system trains several times and after that Cross-entropy together with error rate would indicate how good the results are.

Results and Discussion

The emotions used in the samples are *happy*, *sadness*, *angry* and *neutral*. The below sections contain the corresponding classification results.

Classifier

The network used in the experiment is composed of three layers: the input layer, the hidden layer and the output layer. The input layer takes the 23 feature values for 40 samples of two frames. The hidden layer has 30 nodes and uses a sigmoid transfer function. The number of nodes in the output layer depends on how many emotional categories to recognize. For this research a resilient back propagation training algorithm in the network is used. The advantage of this training algorithm is that it can eliminate harmful effects of the magnitudes of the partial derivatives.

Performance analysis

The below description is the classification result for the trained Neural Network classifier. Two times trained ANN emotions classification shown in Figure 1 and Figure 2. Four emotions are listed together with the error rate for each row and column representing for target class and output class respectively.

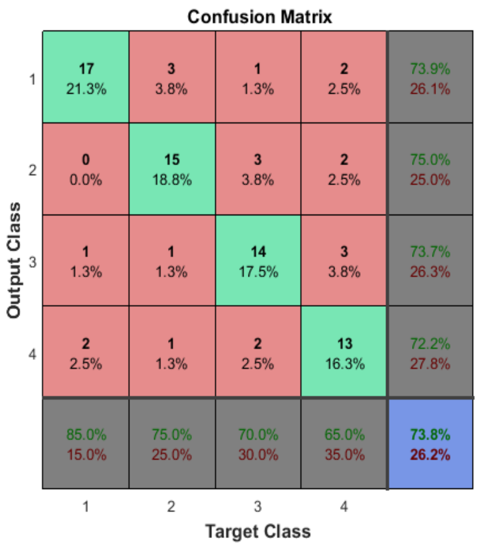

Figure 1: Over all Confusion matrix for two time trained ANN

Figure 2: Three set of data Confusion matrix for two time trained ANN

Therefore, the number in cell “1” stands for how many sad speeches have been classified into the sad output. Cell “2” shows how many angry speeches have been misclassified into the class sad. The performance of classifier improved by increasing the number of training. After the training of the network into ten times, the overall emotions classification result shown as a confusion matrix in Figure 3 and the results of the three data sets shown in Figure 4. Classification results of all four sets of emotions and an overall result are given in tables 1 and 2 below. This gives a clear idea about the classification system.

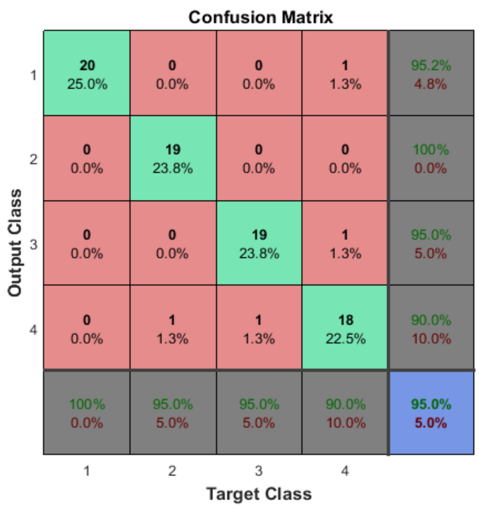

Figure 3: Over all Confusion matrix for ten time trained ANN

Figure 4: Three set of data Confusion matrix for ten time trained ANN

Overall matrix in Figure 1, 17 of sad speeches have been put into the correct output as sad, one sad speech is misclassified into happy speech and two of the sad speeches are misclassified into neutral speech. For the next class, 15 of the angry speeches are classified correctly. Three of angry speeches is misclassified into the sad output, one of them are misclassified into the happy output and one of them into neutral speech. For happy speeches, 14 of speeches are correctly classified and six of the speeches are misclassified output. At last, 13 nature speeches are correctly put into nature output and the rest are incorrect. Table 1 shows the result percentage of classified emotions for two times trained network.

The overall correctly classified emotions are 73.8 % and error rate is 26.2 % as shown in Table 1, then the accuracy of the system needs to be improved.

Table 1: Description of two times trained Network classification result

Emotion	**Sad**	**Angry**	**Happy**	**Neutral**	**Classified**
Sad	17				85.0%
Angry		15			75.0%
Happy			14		70.0%
Neutral				13	65.0%
	Overall				73.8%

Table 2: Description of ten times trained Network classification result

Emotion	**Sad**	**Angry**	**Happy**	**Neutral**	**Classified**
Sad	20				100.0%
Angry		19			95.0%
Happy			19		95.0%
Neutral				18	90.0%
	Overall				95.0%

Then the performance is improved by increasing the training times to ten to let the system reaches an optimal result. In Table 2 shows the results after ten times trained. The overall correctly classified emotions are 95 % and the error rate is 5 % as shown in Figure 3 and Figure 4. The accuracy of the system is improved after increasing the number of training.

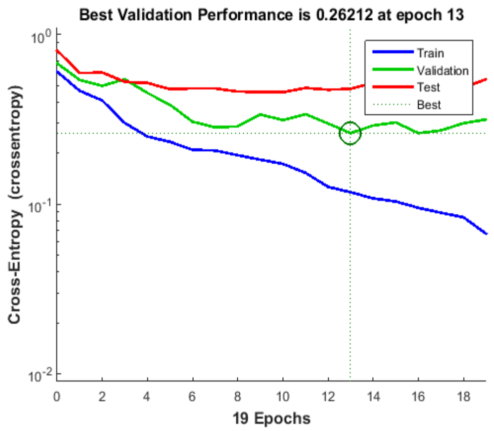

Figure 5: The performance of classifier after two times trained

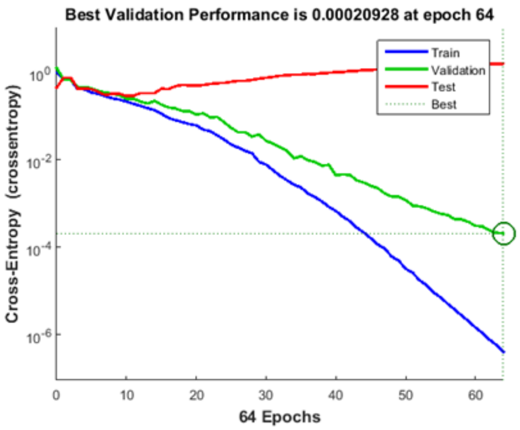

Figure 6: The performance of classifier after ten times trained

In Figure 5 shows the classifier reaches the best validation performance at epoch 13 with the value of 0.26212, where epoch means the number of times for all the training vectors used once to update the weights to the features.

In Figure 6 shows the validation performance of the classifier decreases to 0.00020928 from 0.26212 after the training ten times and the confusion matrix shows a lower error rate as shown in Figure 3 and Figure 4.

Lower values of Cross-entropy indicate that the classification is better. Zero Cross-Entropy means no error. For a new non-trained eight datasets, the classifier classifies the emotions with 87.5 % accuracy as shown in the Figure 7.

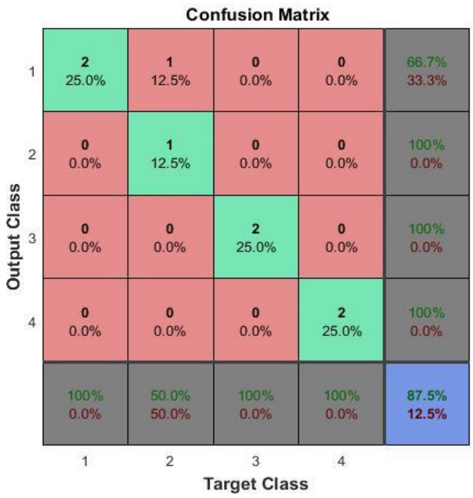

Figure 7: The performance of classifier for new data set

Furthermore, after a suitable number of training process with a low error rate, the neural network classifies completely new eight speech corps. The classification results in terms of error are shown in Figure 7 where two sad speeches are classified as correct; one angry speech is recognized as sad emotion; two happy speeches are correctly classified; two nature speeches are in the nature output and the total classification rate is 87.5 % for the new speech samples.

In this classification, using only short-term features, the rate is better than the result obtained in experimental study on emotion recognition developed 140 utterances per emotional state with both short-term and mid-term feature values [10]. Similarly, comparing with other approaches [1-9] to emotion recognition, the presented results provide higher accuracy with the selected short-term features.

Conclusion

The purpose of this work is to classify the four basic emotions in the speech signals using artificial neural network pattern recognition algorithm and analyze its performance. Artificial Neural Network is a powerful tool for pattern recognition and classification. The chosen short-term features of speech signals are loaded into the system and trained for the target emotions. After suitable number of times of training process, new test signals are loaded into the system for emotion classification and analysis. The selected 23 short-term features are proven to be good representations of emotions for speech signals with a desired accuracy of 87.5 % classification rate for the new data set.

Future Work

In future, the system could be improved by increasing the accuracy of extracted features to classify more complicated speech samples for multiple speakers and more emotions to increase the accuracy of the classifier and develop an automated emotion recognizer. This work could be developed for other spoken languages.

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