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Research Article

A Machine Learning Model for the Classification of Human Emotions

David Ademola Oyemade[1*], Diseimokumor Favour Seregbe[2]

[1]Dept. of Computer Science, Federal University of Petroleum Resources, Effurun, Nigeria
[2]Dept. of Computer Science, Delta State School of Marine Technology, Burutu, Delta State, Nigeria

**Corresponding Author: oyemade.david@fupre.edu.ng,*

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Abstract: Emotions are expressed as part of ordinary speech. Facial expressions, speaking, utterance, writing, gestures and actions are all examples of how humans convey their emotions. Emotions are visible in a large body of research in the domains of psychology, linguistics, social science and communication.as a result, scientific research in emotion has been explored along multiple dimensions and has drawn research from various fields. This paper proposes a model which automatically learns emotions from texts to address the challenge of emotion recognition, noting that language is a powerful tool for communication. We provide automatic recognition in text form of six primary emotions. The use of microblogging was adopted as a rich source of opinion and emotion data. The text under investigation is made up of data gathered from blogs, which reflect writings with high emotional content and hence are appropriate for the study. The first challenge that comes to mind is to create a corpus that is annotated with emotion-related data. Unlike traditional approaches, which rely mostly on statistical methods, we propose a new method which infers and extracts the causes of emotions by incorporating knowledge and theories from other disciplines, such as sociology. The model incorporates Long Short Term Memory (LSTM) machine learning model capable of correctly predicting and classifying human emotions. The results showed that the model produced a 98 percent training accuracy and 88 percent validation accuracy. This concept can be deployed and used in a variety of corporate domains, including marketing, customer support and even the entertainment industry.

Keywords: Machine Learning, LSTM, Classification, Human Emotions, Natural Language Processing

1. Introduction

Emotions have fascinated researchers for long, as is evident in the vast body of research work related to emotion in the fields of psychology, linguistics, social sciences and communication. Human emotion is indicated by facial expressions in voice utterances, writings, ingestions and activities. As a result, scientific research in emotion has been conducted across multiple dimensions and domains. It is noteworthy that language is a powerful tool to communicate and convey information. It is also a means to express emotion. Natural Language Processing (NLP) techniques have long been applied to automatically identify the information content in text [1, 2]. However, because of the diversity of natural language spoken by various people, detecting human emotion is a challenging task. Applications including topic-based text classification, summarization, question answering systems, and information retrieval systems usually concentrate on the information contained in text. In this study, NLP approach is used for the identification of emotions represented in text. In recent years, Artificial intelligence (AI) inspired research has placed a greater emphasis on designing systems that incorporate emotion. Emotions are crucial to several natural processes that are modelled in AI systems. These include perception, reasoning, learning, and natural language processing. Emotion research is important for the development of affective interfaces, that is, those that can make sense of emotional inputs, provide appropriate emotional responses and facilitate online communication through animated affective agents. Such interfaces can significantly improve user experience in computer-mediated communication (CMC) and human-computer interaction (HCI) texts-to-speech (TTS) synthesis system. Emotion-aware TTS systems can identify emotional nuances in written text and accordingly provide more natural rendering of text in spoken form [3].

In recent years, increasing impact of social networks on people's opinions and decision making has attracted lots of attention. Microblogging, a popular social networking program that allows user to share and discuss a variety of topics, is seen as a rich source of opinion and emotion data. Drawing insights from these data can help to improve businesses model, security intelligence and state of happiness/sadness of people in a community, country and even in the general human psychology. Our proposed model applies an innovative method for detecting emotions in microblog entries. We will infer and extract the reason of emotions while importing knowledge and theories from other fields such as sociology.in contrast to traditional approaches which are primarily based on statistical methods. With the huge growth of micro-blogging platforms like Facebook, Twitter, Instagram and WhatsApp there has been an increased interest in detecting sentiments and emotions in large text corpus. The proposed machine learning model will help to draw insights from data obtained from micro-blogging platforms. Fear, anger, joy, surprise, sadness and love have been identified as basic emotions [4, 5]. Emotions are expressed in various means which include movies, audio, speech and text. This research work aimed to create a machine learning model for emotion classification from text and how it impacts on business and the society.

Human emotions play a vital role in our day-to-day life. We may not be able to convey all our thoughts through speech alone. Emotions play their roles in exhibiting one's feelings. Every human being expresses inner thoughts through emotions. By looking at a person's emotional state at a particular situation, one can be able to decide the behavior of that person. Emotional reactions will vary from person to person, everyone will not have the same emotional state during any situation. Recognizing human emotions is crucial because of the society impact of different forms of emotions on relationships [6].

1.1 Emotion Detection

Emotion Detection and Recognition from Text is a new subject of study that is strongly linked to sentiment analysis. Emotion analysis is to detect and recognize type of feelings through the expression of texts while sentiment analysis aims to detect and recognize positive, neutral, or negative feelings from texts. Emotion detection has become very important in most countries in the world. For example, governments and organizations all across the world are increasingly focusing on the happiness index. People's wellbeing is measured by the UK government, other counties and cities such as Seattle, Dubai, South Korea and similar metrics too. Emotion detection in text has become more popular in recent years due to its vast potential application in marketing, political science, psychology, human computer interaction, artificial intelligence and other fields. Access to a huge amount of textual data, especially opinionated and self-expression text also plays a special role to bring emotion to focus. Emotion detection tend to affect the word sets from the basic set of emotions [7].

Detecting emotion from text has become increasingly popular in the domains of neuroscience and cognitive services to study consumer behavior. The task of detecting emotions is akin to assessing the sentiment of a text. In computational linguistics, emotions detection is the technique of identifying discrete expression in text [8]. Emotion Detection can be classified as keyword-based detection and learning-based detection [4, 9]. Keyword-based detection is done by extracting emotional keywords from text that are matched with the knowledge base or dictionary such as thesaurus. Keyword based Detection has a drawback such as inability to discern emotion from a phrase that lacks any emotional keywords, insufficiency of two-language information and ambiguity with definitions of keyword. Learning based detection is a system that is trained to identify the emotion. Deep Learning allows the system to understand the semantics and structure of sentence and also the interdependency of sentence. An initial emotion dataset is created, which is then tagged. This tagged data set is fed to neural network that trains the data set for greater accuracy and the ability to handle new data. There are a variety of training models to choose from, including convolutional neural network and recurrent neural network [8]. After training the neural network analytic reports are generated until desired accuracy is achieved.

1.2 Resources for Detecting Emotions in Text

Some sources of emotion dataset include, labelled text, International Survey on Emotion Antecedents and Reactions (ISEAR) and EmotiNet knowledge base. Labelled text is the Swiss Center for Affective Sciences (SCAS). ISEAR is the most popular resource they offer. It is made up of replies from around 3000 people from all over the world who were asked to describe circumstances in which they felt each of the following seven emotions: joy, fear, anger, sadness, disgust, shame and guilt, and how they reacted to them. The outcome was a promising dataset that could be used to test a variety of emotion extraction and categorization approaches. This dataset contains approximately 7600 records of text that elicits strong emotions. SCAS contains a plethora of resources that can be beneficial in languages other than English. This dataset contains approximately 7600 records of text that elicits strong emotions. SCAS contains a plethora of resources that can be beneficial in languages other than English. The EmotiNet knowledge base uses common sense knowledge of concepts [10]. An emotion word lexicon was created using lexicons for emotions and Amazon mechanical Turk has been used to annotate over 14000 words in English, as well as lexicons in other languages [11, 12]. This paper proposes a model which automatically learns emotions from texts to address the challenge of emotion recognition, noting that language is a powerful tool for communication. We provide automatic recognition in text form of the six primary emotions using Long Short Term Memory (LSTM) deep learning model. Our proposed model applies Emotinet database. Sequel to this, a detailed evaluation and analysis of the model's results are presented. This is part of the unique contributions of this study.

The organization of the remaining part of the paper is as follows: section 2 contains the related work while section 3 explains the methodology. Results and discussion are given in section 4. Section 5 concludes the article.

2. Related Work

In this section a number of documented works on machine learning models for classification of human emotion using text and other related works in this area are reviewed.

John Atkinson and Daniel Campos employed the minimum redundancy maximum relevance (mRMR) techniques for features selection and the support vector machine for binary classification into low/high valence and arousal. The reported accuracy rates for valence and arousal were 73.14 percent and 73.06 percent, respectively. The research was carried out by extracting and analyzing EEG characteristics from the DEAP database [13].

Zahid Halim, Mehwish Waqar and Madiha Tahir described the novelty of a proposed frame work with the utilization of in-text features to identify emotion contained in short texts and development of a dataset for this purpose. The study employed three classifiers and three features selection approaches, all of which are based on machine learning methodologies. There were six emotions in total: happy, sad, surprised, negatively surprised, positively surprised and neutral. These were utilized on the base line theories on human emotion [14].

G. Santhi proposed a system that continuously measures and monitors a patient's emotion using facial expression as part of health provisioning. Patients monitoring was achieved through Internet of Things [15]. Haposan Vincentius Manalu and Achmad Pratama Rifai proposed a hybrid model of convolutional neural network-recurrent neural network for emotion detection through facial expression using video data from Emognition Wearable Dataset 2020 [16]. Pavel Kozlov, Alisher Akram, and Pakizar Shamoi proposed a framework for detecting emotions in video games for children by analyzing the audio and video using facial expression recognition dataset combined with fuzzy logic inference approach. The framework consists of feature extraction from the video data while a fuzzy inference system performs the fusion [17]. Asia Samreen and Syed Asif Ali presented a dataset for human behavior analysis to verify the accuracy of online translation between Roman Urdu and English language and to address the challenge of interpreting mixed codes for emotions. An emotion lexicon was used for the dataset construction [18].

Zhiwei Liu, Tianlin Zhang, Kailai Yang, Paul Thompson, Zeping Yu and Sophia Ananiadou reviewed the various emotion-based methods for detecting misinformation such as fake news and rumour as it affects netizens, focusing on advanced fusion methods [19]. Bingtao Wan, Peng Wu, Chai Kiat Yeo and Gang Li combined Bidirectional Encoder Representations from Transformers (BERT) technique with emotion cognitive reasoning (ECR) to tackle the challenge of sentiment analysis of online public opinion on emergencies such as port explosion or COVID-19 pandemic which affect social stability [20]. Carmen Bisogni, Lucia Cascone, Michele Nappi and Chiara Pero proposed a method which tackled emotion recognition problem by distinguishing between spontaneous and posed expression. Modified Partitioned Iterated Function Systems (PIFS) was then used to generate a Fractal Encoding for facial emotion recognition [21]. V. Preethi, Nimisha Jadav, Komal Shirsat and Mohan Bonde proposed a text-based emotion recognition model using Long Short Term Memory algorithm and analyzed the system by using tweets [22]. However, a detailed analysis of their results was missing. Our proposed model applies Hugging face dataset to LSTM and gives a detailed analysis of the results of the investigation. This is our contribution to knowledge and the uniqueness of this paper.

3. Methodology

Long Short Term Memory (LSTM) machine learning algorithm is adopted in this study. LSTM is a variation of Recurrent neural network (RNN) model. An RNN can only memorize short-term information, but LSTM can handle long time-series data. Moreover, an RNN model has the vanishing gradient problem for the long sequence data but LSTM can prevent this problem during training. An LSTM model has automatic control for retaining relevant features or discarding irrelevant features in the cell state. An LSTM model has three gates to control features, that is, the input gate, forget gate, and output gate. The input gate controls new information to flow into the cell state. The forget gate removes previous unimportant information from the cell state. The output gate regulates extracted information from the cell state and then decides the next hidden state. An LSTM model can automatically save or remove stored memory using these gates [23]. The LSTM model architecture is shown in figure 1.

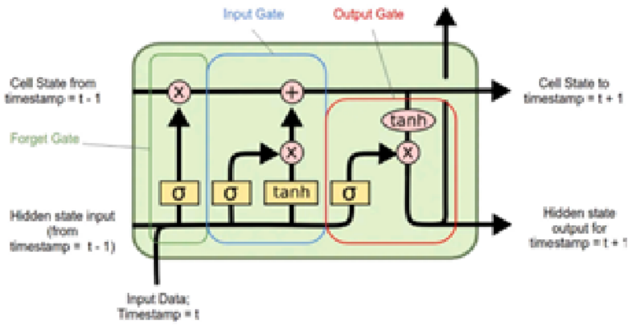

Figure 1. LSTM Model Architecture [23]

3.1 Precise Method

The precise methodology for this study consists of five phases which include input datasets, pre-processing, splitting dataset, training and model evaluation.

The input datasets are obtained from a microblogging site. An extract from Twitter dataset are used for this purpose, using Hugging Face. For pre-processing, this study leverages on pre-processed tweets for NLP analysis from Hugging Face, obtainable from hugging face website. This saves the time of data cleaning and data pre-processing operations while concentrating on the building of the machine learning model. However, the tweets are tokenized, the lengths of the tweets are checked and padded sequences are created. Hugging Face is currently the largest hub of ready-to-use NLP datasets for ML models with fast, easy-to-use and efficient data manipulation tools.

The dataset is split into train set and validation set. The dataset is used for training the model and thereafter tested with the validation data to check the machine learning model's accuracy. The entire process is created using TensorFlow deep learning framework. TensorFlow is a complete open-source deep learning framework. It has a very rich and flexible ecosystem of tools, libraries, and community resources that enable researchers to push the boundaries of Machine Learning and it allows developers to easily build and deploy ML-powered applications. The LSTM deep learning algorithm is implemented with python programming language and associated libraries, which contains tools for model creation, training, validation and testing.

3.2 Model Creation Process

This section illustrates the various steps taken to create the model. A virtual environment on the Jupyter Notebook using the Anaconda PowerShell console Window was employed. The python programming language was used for this purpose. TensorFlow 2.2 was installed on the environment created. The various libraries/dependencies were installed using the anaconda PowerShell into the TensorFlow.

The steps involved in the model creation are summarized as follows:
Step 1. Installation of Hugging Face's NLP package and importation of libraries.
Step 2: Importation of the tweet Emotion dataset, creation of the train and the validation test sets and extraction of tweets and labelling of the dataset.
Step 3: Tokenization of the tweets.
Step 4: Checking of the length of the tweets and creation of padded sequences.
Step 5: Labels preparation
Step 6: Creation and compilation of the Model
Step 7: Model Training
Step 8: Model Evaluation and Visualization
Step 9: Evaluation of the model's performance using confusion matrix.

3.3 Scoring function

To assess the model performance, we utilize the Scikit learn scoring function. This function takes two arrays as input. First, an array of the independent variable, second an array of the dependent variable. The score is normally between 0 and 1, in which case 0 is poorly accurate and 1 is significantly accurate.

3.4 Materials

All the experiments were conducted using python programming language in a Windows PC. It was developed with a focus on enabling fast experimentation. It contains lots of Libraries to aid the success of this study. The system was implemented with an HP 2000 Notebook PC windows 10 operating system with a Processor of Intel core i3, having a RAM size of 4 GB 2.20 GHZ HDD 500 GB. The software tools employed cut across frameworks, libraries and integrated development environment. They include Keras library, Natural Language Processing, Matplotlib, Numpy and Pandas.

The data flow of the model design is shown in figure 2. The data goes through various processes from 'Read Input File' to 'Write Results' as shown in figure 2.

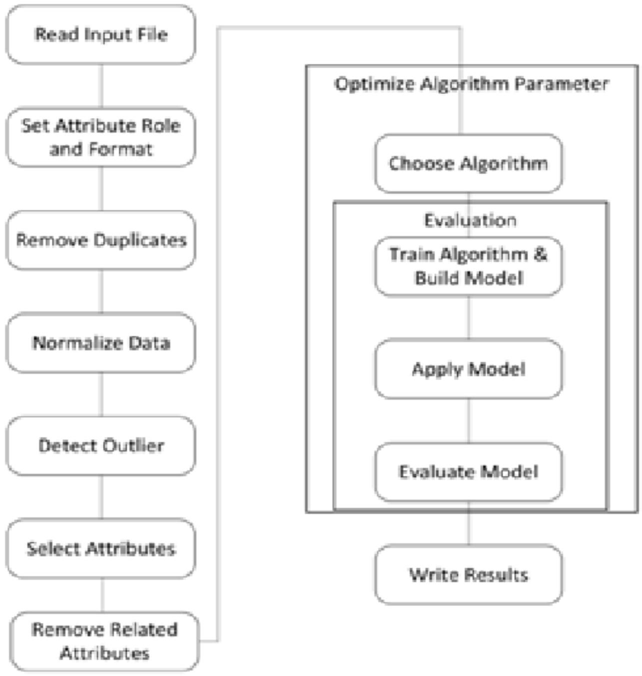

Figure 2. Data flow of the Model Design

4. Results and Discussion

This section gives an overview of the achieved results, the dataset used and the experiment process to answer the given research questions. The following questions will be answered in detail: What is the source of the dataset? What is the size of dataset used for training, testing and analysing the algorithms? Which tools were used to create the deep learning model? What is the accuracy level of the model created? What is the model evaluation score?

4.1 Data Analysis

Using LSTM as the baseline model, 160,000 train samples, 20000 validation samples and 20000 test samples were used. The lengths of each tweet in the dataset was checked and visualized as in figure 3.

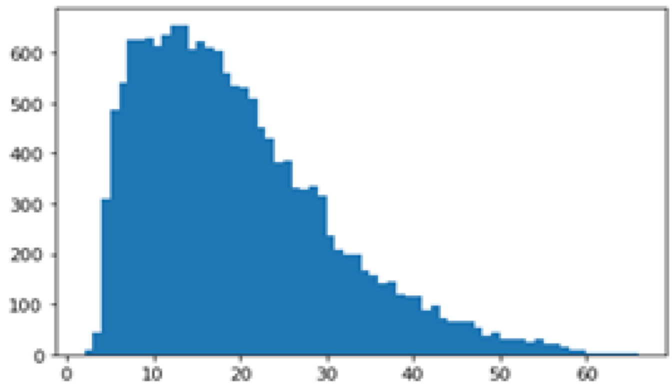

Figure 3. The lengths of each tweet in the dataset

The dataset has six classes of emotions as visualized in figure 4. The six emotions are pictured as sadness, anger, love, surprise, fear and joy. It can be seen from figure 4 that joy has the highest value of data while surprise has the lowest value.

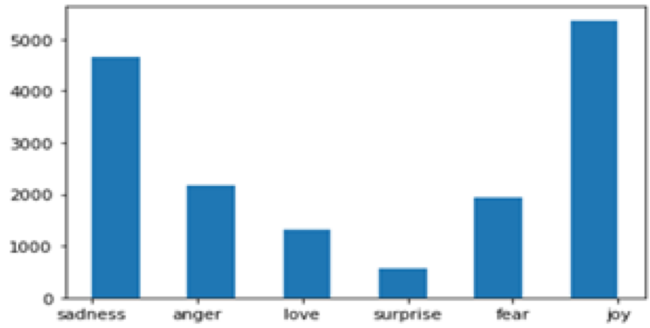

Figure 4: The Classes of Emotion Visualized

The snapshot of the model training is shown in figure 5 for eight epochs. For each iteration during the training, figure 5 shows the time, loss, accuracy and loss value.

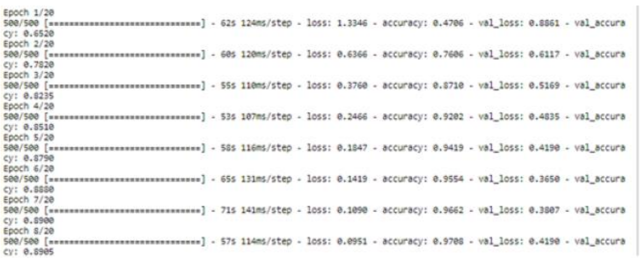

Figure 5: The Model training results for 8 epochs

The evaluation of the training accuracy is shown in figure 6. The model showed 98% accuracy on training and 88% accuracy on validation as seen in figure 6.

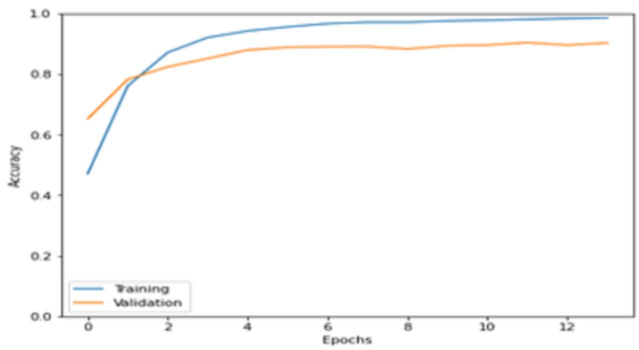

Figure 6: The Model Accuracy on training and validation

The percentage loss on training and validation is illustrated in figure 7. This figure shows the sum of errors and the accuracy of model prediction in comparison to true data.

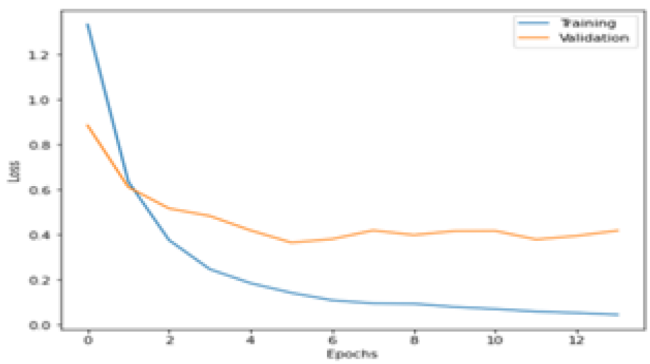

Figure 7: The Percentage loss on training and validation

The classification confusion matrix of six emotions and the confusion matrix showing the predicted values in plain form are illustrated in figure 8 and figure 9 respectively.

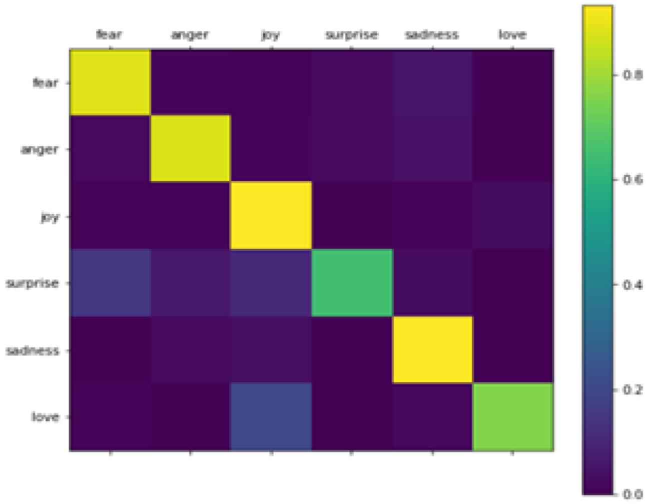

Figure 8: The classification confusion matrix of six emotions

```
array([[ 40,   4,   6,  16,   0,   0],
       [  1, 527,  25,   5,   4,  19],
       [  4,   5, 623,   3,  48,  12],
       [ 13,  12,   0, 190,   3,   6],
       [  2,   5,  25,   2, 118,   7],
       [  0,  18,   4,  10,  14, 229]], dtype=int64)
```

Figure 9: Confusion matrix showing the predicted values in plain form

From the confusion matrices, it can be seen that Fear and Anger have the highest level of accuracy. Sadness and love have the lowest. In the dataset used in the training, our model has six classes. The emotion classes have been indexed as key-value pair as follows: {0: 'surprise', 1: 'sadness', 2: 'joy', 3: 'fear', 4: 'love', 5: 'anger'}. It implies that 0 represents surprise, 1 represents sadness, 2 represents joy, 3 represents fear, 4 represents love and 5 represents anger. The model classification report below gives a clear picture of how the model has perform for the six emotions classes used in this research work.

4.2 Model Classification Report

The various key terms used in the classification report are explained as follows: Precision indicates the proportion of positive identifications (model predicted class 1) which were actually correct. A model which produces no false positive has a precision of 1.0. Recall indicates the percentage of true positives that were correctly classified. A model with a recall of 1.0 produces no false negatives. The F1 score is a combination of precision and recall. Every perfect model achieves an F1 score of 1.0. Support refers to the number of samples each metric was calculated on. Accuracy refers to the accuracy of the model in decimal form. A perfect accuracy is equal to 1.0. Macro Avg is an abbreviation for macro average, which is the average precision, recall, and F1 score across classes. Macro avg does not account for class imbalances in effort, so if they occur, attention is paid to this metric.

Weighted avg is an abbreviation for weighted average. It is the weighted average precision, recall and F1 score between classes. Weighted average means each metric is calculated with respect to how many samples are in each class. This metric will favor the majority class (for example, the weighted avg will give a high value when one class out performs another due to having more samples). The classification report for the model is given in figure 10.

```
              precision    recall  f1-score   support

           0       0.67      0.61      0.63        66
           1       0.92      0.91      0.91       581
           2       0.91      0.90      0.90       695
           3       0.84      0.85      0.84       224
           4       0.63      0.74      0.68       159
           5       0.84      0.83      0.84       275

    accuracy                           0.86      2000
   macro avg       0.80      0.81      0.80      2000
weighted avg       0.87      0.86      0.86      2000
```

Figure 10: The classification report for the model

The classification report shows a Model Accuracy of 86% and support of 2000. Macro avg. showed 0.80 for precision, 0.81 for recall and 0.80 for F1 score. Weighted avg showed 0.87 for precision, 0.86 for recall and 0.86 for F1 score. Surprise which has index of 0, has precision of 0.67, recall 0.61, F1 score of 0.63 and it was calculated with 66 training samples. These values are not impressive; hence the model did not predict surprise very well. Sadness which has index of 1, has precision of 0.92, recall 0.91, F1 score of 0.91 and it was calculated with 581 training samples. These values are very closed to 1.0. The model did well in predicting sadness. Joy which has index of 2, has precision of 0.91, recall 0.90, F1 score of 0.90 and it was calculated with 695 training samples. These values are very closed to 1.0. The model did well in predicting Joy. Fear which has index of 3, has precision of 0.84, recall 0.85, F1 score of 0.84 and it was calculated with 224 training samples. These values are very closed to 1.0. The model did well in predicting Fear. Love which has index of 4, has precision of 0.63, recall 0.74, F1 score of 0.68 and it was calculated with 159 training samples. These values are not very closed to 1.0. The model did not do quite well in predicting love. Anger which has index of 5, has precision of 0.84, recall 0.83, F1 score of 0.84 and it was calculated with 275 training samples. These values are closed to 1.0. The model did quite well in predicting Anger. Table 1 shows the comparative analysis of the research results.

Table 1. Comparative Analysis of Results

Model	Accuracy %	Precision	Recall	F1-score
Logistic Regression (Char+Word Tfidf)	0.91	0.92	0.92	0.92
Multinomial Naive Bayes (Char+Word Tfidf)	0.85	0.83	0.83	0.78
Xgboost (TFIDF+NLP Features)	0.85	0.89	0.90	0.89
CNN+BiLSTM	0.84 .9	0.80	0.85	0.82
CNN+LSTM (fastText wordvector)	0.85 .7	0.81	0.86	0.83
The Proposed LSTM Model	0..86	0.87	0.86	0.86

Comparing our results with the report of the classification of different ML and DL models of the work done by Rahul Venkatesh Kumar, Shahram Rahmanian and Hessa Albalooshi [24], Table 1 shows that our proposed LSTM deep learning model with a model accuracy of 86% performed better than the Naive Bayes, Xgboost, CNN+BiLSTM and CNN+LSTM. However, logistic regression performed better than our created model.

5. Conclusion and Future Scope

Understanding human Emotions has gained the attention of researchers and practitioners alike. Employees can no longer be viewed as biological machines capable of leaving their feelings, norms, and attitudes at home when they go to work. Researchers and tech giant like Microsoft, Google, Apple and major universities across the world are making effort to understand human emotion in various levels as a result of its connection with staff performances, service output, sales, revenues generated, quality of service provided, customer commitment, employee staffing and retention, employee commitment, employee health and gratification, and self-confidence. In this paper, we have identified the need to create a model with a high level of accuracy that can classify human emotions correctly. Although, several traditional machine learning algorithms like support vector machine and KNN among many others, have been used to classify emotions, and their results have not been very impressive. In this regard, this study work has adopted a deep learning approach. An LSTM deep learning algorithm has been used to create our emotion classification model. After training the model with the datasets, the performance was impressive. The model has an accuracy level of 98% on our training set and 88% accuracy on validation set. Although, the model classification reports have an overall accuracy of 86%. Detecting human emotion is a difficult task because of the complexity of the way the natural language is spoken by different people. This research work focused on creating a deep learning model with high level of predicting/classifying human emotion correctly. In future, our proposed model can be deployed for several business domains which may include marketing, customer service and even entertainment industries.

Data Availability
The data will be made available on demand.

Conflict of Interest
The authors declare that there are no conflicts of interest.

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Authors' Contributions
David Ademola Oyemade reviewed the article and wrote the related works. Diseimokumor Favour Seregbe wrote the first draft of the manuscript as a dissertation.

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AUTHORS PROFILE

David Ademola OYEMADE is an Associate Professor of Computer Science at the Federal University of Petroleum Resources, Effurun, Delta State, Nigeria. He holds a PhD degree in Computer Science obtained from the University of Benin, Benin City, Nigeria in 2014. He is a life member of Nigeria Computer Society (NCS) and a professional member of Association for Computing Machinery (ACM). He has served as a lecturer in the Department of Computer Science, Federal University of Petroleum Resources, Effurun and rose through various ranks. He has supervised several students of at undergraduate and postgraduate levels at the department of Computer Science, Federal University of Petroleum Resources, Effurun. He has many articles in international and local journals. His research area is Software Engineering, Software Architecture, Intelligent Systems and financial market algorithms and modelling.

Diseimokumor Favour Seregbe earned her B.Sc. and M.Sc. in Computer Science from Niger Delta University, Amassoma, Bayelsa State in 2011 and Federal University of Petroleum Resources, Effurun, Delta State, Nigeria in 2022 respectively. She is a member of IAENG. She a lecturer in the Department of Computer Science, Delta State School of Marine Technology, Burutu, Delta State Nigeria. Her research interest is Artificial Intelligence.

