EMOTIONAL ANALYSIS

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Submitted by

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Date: 13-Dec-22

This is to certify that the work present in this Project entitled "**EMOTIONAL ANALYSIS**" has been carried out by **T.Roshitha, N.Mounica, A.Kavyasri, A.Praneeth,** under my supervision. The work is genuine, original, and suitable for submission to the SRM University – AP for the award of Bachelor of Technology/Master of Technology in **School of Engineering and Sciences**.

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Abstract

Emotions play a very important and crucial role in everyone's life. They are the fundamental component in our lives. So understanding these emotions helps us to understand the relationship between people. Analysis of these emotions plays an important role in understanding the behaviour and mental state of the people. Emotion can be of different types like happiness, sadness, anger, surprise, fear and many more. One of the difficult and newly-emerging problems in the field of natural language processing is emotion detection and analysis. Recognizing emotions can be done from facial and audio records, and through textual data also. Neuroscience, data mining, psychology, human-computer interaction, e-learning, information filtering systems, and cognitive science are just a few of the domains where the study of emotions can be used in the advancement of the field of emotions. This paper provides a summarization of existing methods, approaches that helps us to understand the emotion analysis. We tried to implement the dataset of amazon book review by using LSTM (long short term memory) with an accuracy of 80%.

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1.Introduction

The emotional analysis is a crucial aspect of affective computing. "Affect" refers to emotion, and the verbs to compute or measure are used. It just takes affective computing for us to develop the instruments or systems that process, recognise, interpret, and mimic human affects, enabling us to research how humans and computers interact. These data examples include text, voice, and expressions on the face. By examining the comments or feedback customers leave, businesses can learn a lot about how satisfied their clients are with their services. Analysis of the feelings and attitudes expressed in diverse textual data transmitted via the Internet has its own relevance. For instance, it can be used to gauge a community's wellbeing and prevent suicides, and also it can be very helpful for individuals.

Sentiment analysis, also referred to as opinion mining, is a machine learning and NLP technique. It can analyse how an author uses emotion to convey meaning in any text, as its name implies. Businesses use sentiment analysis tools to assess the sentiment value of their brands, goods, or services. Customer feedback analysis is one of the most frequently used applications of sentiment analysis. The feelings and attitudes of clients can be examined and evaluated using sentiment analysis software. Big organisations use sentiment analysis to do market research, monitor brand and product perceptions, evaluate customer experiences, and gauge public opinion. Sentiment analysis can help you define your target market, develop and implement a marketing strategy, improve customer service, handle crises, and increase sales income, among other things. Both sentiment analysis and emotion analysis have revolutionised how people respond to new things. Content creators can enhance the user experience and reputation of their business by reacting with personalised offerings. This is possible thanks to sentiment analysis and emotion analysis.

This paper is based on previous fieldwork of text-based emotion analysis, which is a new field with numerous real-world applications There has been a lot of work done in the field in the past, and research is still ongoing.on, in particular, using Tweet data.

However, text emotion analysis introduces some difficulties into our work because emotions and the ways in which they are expressed are all subjective. To determine the emotions hidden in a text, Natural language processing, text analysis, and a range of computational methods are used in emotion analysis. At several levels, such as document, sentence, word, and aspect, this analysis can be done.

2.Computational Approaches using Emotional analysis

All the methods used to create and use an emotional classifier are included in the computational methodologies. As illustrated in figure 1 below, they may be generally divided into two categories: lexicon-based approaches and machine learning approaches. A knowledge base having textual units tagged with emotional descriptors is called an emotion lexicon. They rely on lexical resources like dictionaries, word banks, and ontologies. The system is trained using machine learning algorithms, whereas machine learning techniques employ them to map a function for future classification of emotion analysis.

2.1 Lexicon-based approach

One method or set of procedures for performing semantic analysis is the lexicon-based approach. This method establishes the sentiment orientations of the full text or collection of sentences using the semantic orientation of lexicons. Semantic orientations may be positive, negative, or neutral. There are two different methods.

2.1.1 Dictionary-based approaches

The dictionary-based algorithms classify the phrases in the data using a variety of metrics, including term frequency, word count (referred to as statistics), or word synonyms (known to as semantics), among others. They begin with a predetermined lexicon of emotive words. Latent Semantic Analysis (LSA), and even its version, are used by the majority of statistical approaches to analyse the relationship between a set of documents and the terms contained in these documents in order to create meaningful patterns connected to documents and words. The dictionary method is cheap, but validating a dictionary might be difficult.

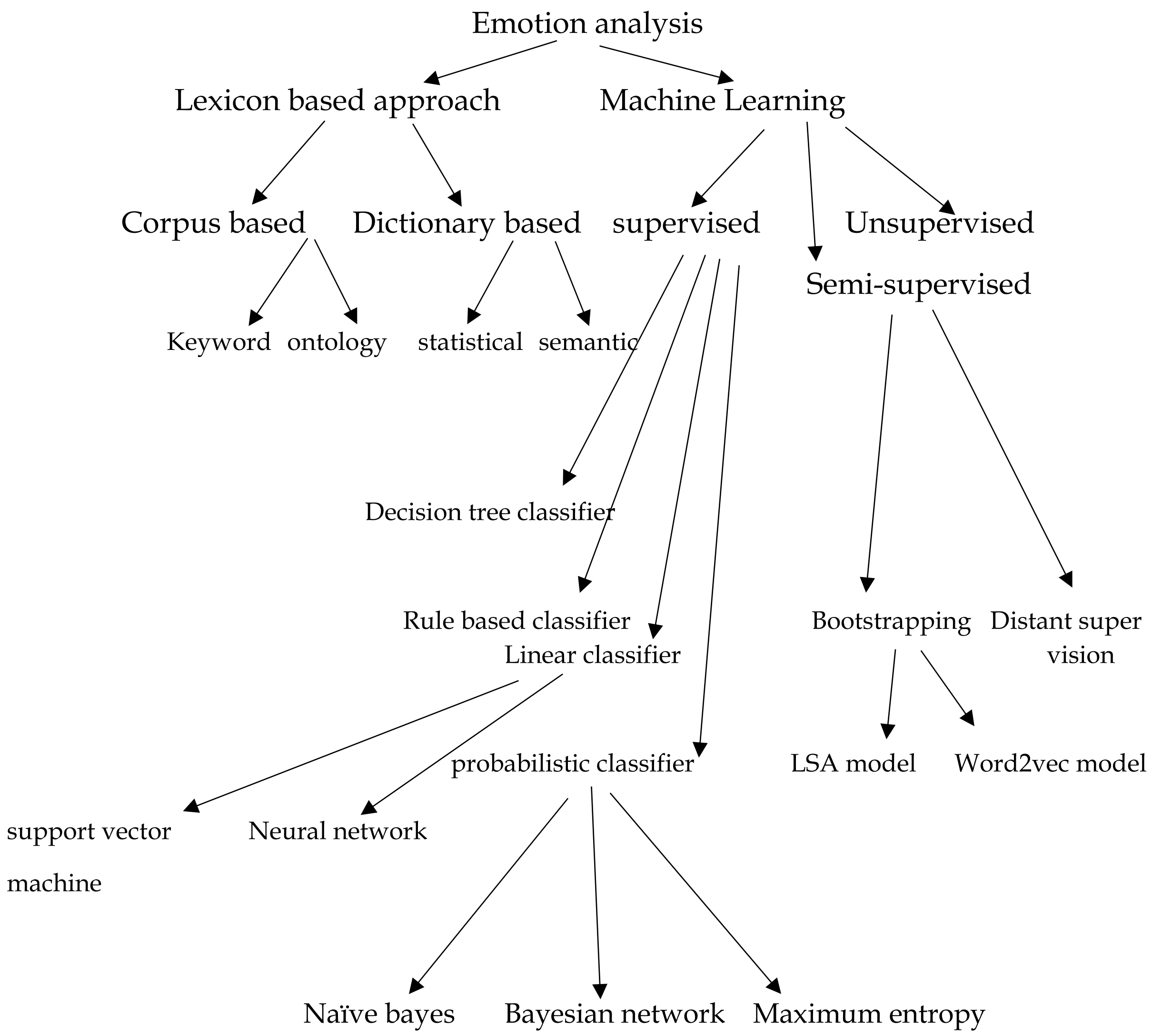

Figure 1. Computational approaches using emotional analysis

2.1.2 Corpus-based approaches

Any generic data can be used in the corpus-based method for emotion analysis. Here, the corpus (data) is initially annotated by adhering to a set of theoretical guidelines for managing a natural language emotion analysis that were taken from a book. In order to categorise the text into different emotional categories, keyword-based techniques construct a collection of predetermined phrases. Utilizing WordNet-Affect, Strapparava. also for examining the headlines' use of emotive language. The EmotiNet and terminology relationships are used in ontology-based approaches to represent situations as a series of acts and their related emotional effects. This strategy is also used for precise emotion recognition.

2.2 Machine learning strategy

Algorithms used in the machine learning technique can learn from data by utilising the linguistic properties of text.

The remainder of them are divided as follows:

2.2.1 Supervised machine learning

These algorithms build a function based on the input data and decide how to use this function to convert the future data to the correct output. The SVM is a conventional strategy in this regard. Few researchers have switched from these traditional methods to more reliable and successful ones like CRF. The supervised learning models also comprise the following; Decision tree classifiers use a hierarchical recursive decomposition of training data depending on the value of the features up until a specified number of leaf nodes that hold values for classification; Rule-based classifier: Using this method, classification is done according to a set of rules. The class labels are represented on the rule's left side, and the conditions in the disjunctive normal form on the features are shown on the rule's right side. Decision tree classifiers use a hierarchical recursive decomposition of training data depending on the value of the features up until a specified number of leaf nodes that hold values for classification; Rule-based classifier: Using this method, classification is done using a set of rules. The class labels are represented on the left side of the rule, while the conditions in the disjunctive normal form on the features are represented on the right side; A linear classifier classifies the emotions by making a determination based on the value of a linear combination of the input text's attributes. These characteristics are also known as feature values and are represented as feature vectors, which are vector images. It has a number of potential models, including neural networks and support vector machines; The probabilistic classifier gives the likelihood of selecting a specific term for each class, assuming that each class is a part of the mixture.

Additionally, it incorporates the classifiers given below: utilising the Nave Bayes classifier, which calculates the posterior probability depending on how words are distributed throughout a document. The maximum entropy algorithm uses an acyclic graph with nodes that represent random variables and edges that denote conditional dependencies, while the Bayesian network uses encoding to convert labelled feature sets into vectors. The weights that were computed for each feature by this vector are then added to yield the class for each feature set. compares the classification of emotions into flat and hierarchical groups.

2.2.2 Unsupervised machine learning

Through the use of these methods, latent structures in the input data are revealed, allowing unlabeled data to be mapped to emotion classes.

2.2.3 Semi-supervised machine learning

There are many known works where labelling is done automatically with the use of hashtags, etc. Semi-supervised algorithms use the automated labelling notion and take one of the two following paths: entrepreneurship and remote supervision.

3 Emotional analysis using deep learning algorithms

Except for the conventional methods, every strategy for classifying emotions fared better than every other technique. To achieve this, we created CNN-based frameworks that utilised the same amount of resources and ran at the same pace regardless of the type of operation. We provide the results of our embedded system-operated thin network, eXnet, demonstrating how well real-time devices perform.

3.1 Naive Bayes Algorithm (NB)

In many cases, classification tasks are carried out using a straightforward Bayesian classifier that makes regular assumptions. As they are widely employed in probabilistic machine learning models, naive Bayes classifiers are frequently used. We use mathematical proof to arrive at conditional probabilities using Bayes' theorem. Figure $2A_1C$ depicts the fundamental layout of NB. The Bayes theorem is used to calculate the likelihood that "A" will occur if "B" has already happened. This diagram shows a hypothesis (A) and evidence (B). Naive Bayes assumes that characteristics and predictors are unrelated when creating a Bayesian model. Or, to put it another way, the attributes have nothing to do with one another. Furthermore, it is also referred to as naïve. One of the four Naive Bayes approaches is Naive Bayes. To classify emails as "spam" or "not spam" is one of the Bayes theorem's many useful applications in computer science. We review the multinomial Naive Bayes method in this article.

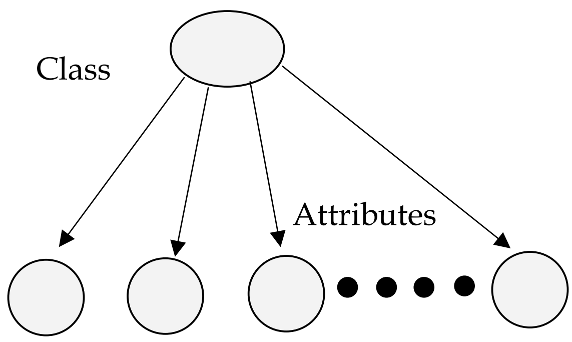

Figure 2. Basic Structure of NB

3.2 Support Vector Machine

The novel Support Vector Regression method was built on the Support Vector Machine (SVM). Margin is not taken into account by linear regression, however it is in SVR. It is impossible to claim that the mainline or its total cannot reach a specific location in space because they are both capable of doing so. Reduce your efforts in the effectiveness class,

$$= 1\ 2\ \|W\|\ 2 + C \sum_{i=1}^{n\cdot} (\varepsilon i\ +\ \varepsilon i\ *)$$

Condition 1:

$$yi - wxi - b \leq \varepsilon + e_i$$

$$wxi + b - yi \leq \varepsilon + e_i^*$$

$$Where\ e_i\ ,_i^* \geq 0$$

The phrase "sum operation" is used to describe the margin idea. The dimensions of the space have a complete bearing on where the search vector is located. In spaces with linear dimensions, the formula is valid. We live in an 8-dimensional space since there are eight variables. The radial basis function (RBF) kernel is utilised throughout the computation using the RBF kernel. Figure 3 illustrates the categorization process's error calculation.

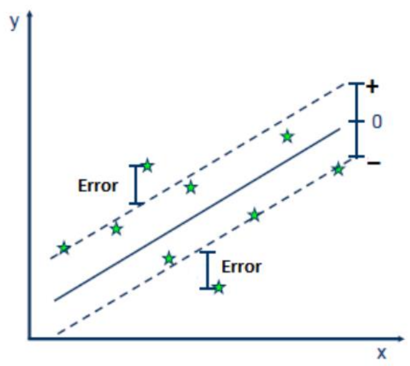

Figure 3. Error Calculation in Classification Process

3.3 Decision tree algorithm

The decision tree technique represents decisions and their potential outcomes in a tree-like graph. consequences, such as the results of unforeseen circumstances, resource costs, and utility. The form of a tree is employed to determine a classification function that, given the values of the attributes, predicts the value of an input qualities (variables). The Decision Tree, which divides labelled datasets into smaller datasets, is used to classify data. Quinlan asserts that this is the situation. After the dataset has been divided into several datasets, the final dataset will only contain things that are highly connected. The distinct subcategories in this procedure are all linked to inquiries that have specific replies to. The evaluation identifies the subset of the new data that meets the requirements. The decision tree's basic tree structure is shown in Figure 6.

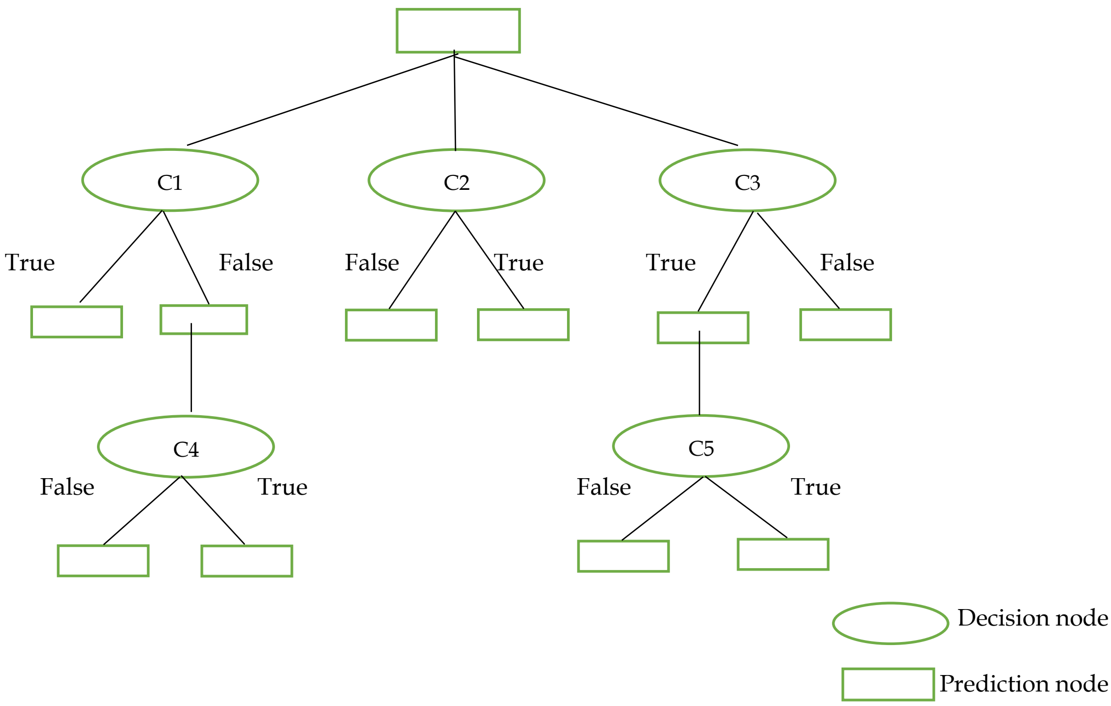

Figure 4. Basic Decision Tree Algorithm Structure

3.4 Random Forest

Using supervised learning techniques, random forests and random decision forests are utilised for classification and regression. When a decision tree has numerous tree instances, it is referred to as a "forest." A decision tree ensemble is constructed during the training phase. The goal class (classification) is then determined by the ensemble's choices, which are either the mean forecast of all the individual trees (regression) or the majority vote of the decision trees. Since the size of the forest has an effect on how well the Random Forest algorithms perform overall, they provide exceptional accuracy and are resistant to overfitting.

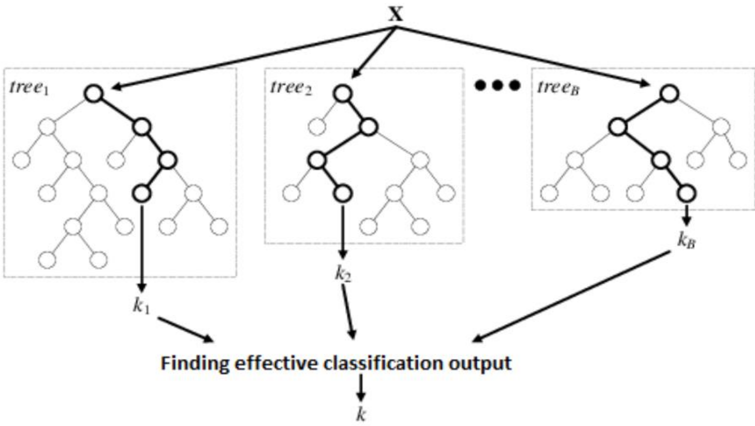

Figure 5. Effective Classification of RF

Using decision trees to bootstrap training samples produces a random forest's tree structure. The decision tree splitting is done at random on a set of characteristics and predictors rather than on the complete collection. In this study, ten estimators from the Random Forest technique are used. Figure 5 depicts the tree structure of the RF output for effective classification.

3.5 Convolution neural network (CNN)

Many computer vision models have shown excellent results with the recent boom in deep learning using Convolutional Neural Networks CNN. CNNs (55-layer deep learning networks) perform better than other machine learning techniques thanks to their remarkable architecture. It is possible to refer to the additional hidden layers as "feedforward neural networks" or "CNNs with hidden layers." By removing features from the data using hidden layers, CNN develops a representation from it. On many layers, pooling and convolutional layers are frequently observed. The fundamental block diagram of CNN's classification process is displayed in Figure 6.

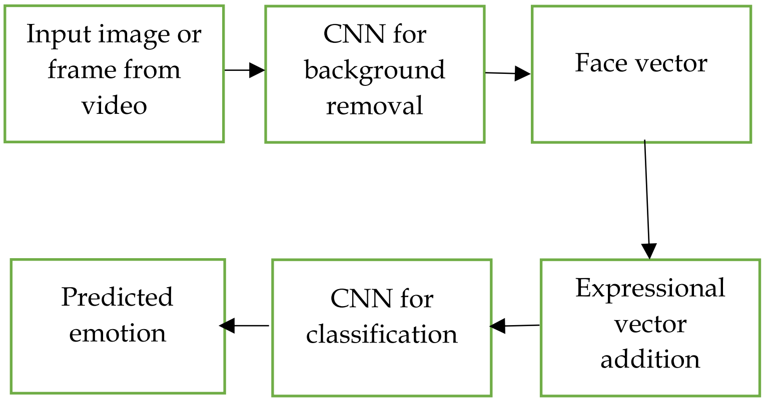

Figure 6. Basic Classification Procedure by CNN

Comparable to CNN, the convolutional layer makes up about 80% of the CNN image. Each of the convolutional layers that the data passes through has a filter (Kernels).The filters' starting point is data, which is combined with filtered data to create a feature map that links the two.

The output of the convolutional layer is a stack of feature maps that are created when several filters are applied to the input. As a result, during the training phase, filter values are learned. When performing the convolution technique, you could obtain local information about the dependence or meaning. Rectified linear units (RLUs) are a method for implementing nonlinearity in CNNs that are used to build feature maps. After convolution, a pooling layer is applied to lower the number of samples in each feature map while maintaining the most crucial data.

The pooling layer reduces overfitting while cutting training time. The most frequent type of pooling is max pooling. Convolutional layers are frequently interleaved with pooling layers in CNN topologies, which are then followed by numerous fully linked layers. Larger number of layers and fewer parameters are the main contributors to fast hardware performance. Actually, by broadening network functionality within the confines of Occam's razor, this helps. To maximise the performance of our system, we also employ a variety of well-known data augmentation techniques, each of which only calls for a single extra connection in our network.

3.6Addition of Effective process

3.6.1 Expression Network (eX-net)

eXnet is often divided into three feature extraction steps. The characteristics that will be extracted in the subsequent step are extracted during the intermediate feature extraction phase. Our network, however, possesses sparsity because of parallel extraction. When you reach the final phase, sometimes known as the conclusion, the procedure is finished. The procedure will be completed once you arrive to the verdict. Since the eXnet design has fewer layers and characteristics, it is more suited for rapid prototyping and early design cycles. Any well-known data augmentation techniques, all of which just require a single additional link in our network, will perform at their best oot of their system when combined with the deep neural network for emotion categorization.

3.6.2 Efficient activation function (EAF)

This stage involves convolution, max pooling, and batch normalisation. Batch normalisation is the next step, and then the Rectified Linear Unit (ReLU), which is also referred to as the Rectified Linear Unit (ReLU) (Convolution Batch-normalization ReLU). We are encouraged to go above and above when planning the pooling process by our lightweight network.

3.6.3 Effective feature extraction (EFE)

We advocate using the Inception Net model to extract parallel features and other types of features. It builds two identical ParaFeat blocks for each instance to simulate the way the brain analyses information. One of these blocks is configured to process data alternately, while the other is configured to receive input serially. Route A and Route B both pass over 1x1, 3x3, and identical convolutions. to reduce the number of parameters to a minimum for both (1x1) convolution-based routes. The 1*1 convolution demonstrates how to reduce parameters with this filter, even though it is just one of the many advantages of using this convolution filter.

Table1 below lists some of the earlier research in the area.

TABLE1: SUMMARY OF PREVIOUS WORK

Article	Year	Author	Method Used	Accuracy	Dataset	Future work
Emotional Analysis Based on Deep learning with Application to Research on Development of western culture	2022	Chen M	BERT-BilSTM	84.45%	Text dataset of literary works	To enhance the model's performance even more, think about including an attention mechanism.
Deep learning for emotion analysis in Arabic tweets	2021	Enas A. Hakim Khalil, Enas M. F. El Houby & Hoda Korashy Mohamed	BiLSTM	93%	SemEval2018 Task1 dataset	Future improvements in preprocessing, such as removing ambiguity results from stemming the nouns ending with, ن,ين usually as a مثني, and words ending with ون,ين as جمع plural, and applying more restricted grammatical rules.
Deep learning approach to text analysis for human emotion detection from big data	2022	Jia Guo	DLSTA approach	97.22 - 98.02%	-	will include on emotion detection, simulating the intensity of the feelings, allowing several emotion classes to operate simultaneously, and researching alternate emotion class models..

A review on sentiment analysis and emotion detection from text	2021	Pansy Nandwani & Rupali Verma	Lexicon Based technique	95.5–99.8%	SemEval, SST, ISEAR datasets	Additionally, the impact of utilising various deep learning models, such as CNN, will be examined.
Deep convolutional image retrieval : A General Framework	2018	Maria Tzelepi and A. Tefas	CNN	77.0344%	Paris 6k UKBench	-
Hierarchical versus Flat Classification of Emotions in Text	2010	Diman Ghazi, Diana Inkpen and Stan Szpakowicz	Hierarchical classifier, SVM	98%	Alm's and aman's Dataset	In the future, each task will have its own specification.
Multi-Class Twitter Emotion Classification: A New Approach	2012	R C Balabantaray ,Mudasir Mohammad and Nibha Sharma	Supervised learning (multi class SVM)	73.24%	Blog (dataset domain)	Utilize more system features and make an effort to take advantage of greater dependence relationships.
Deep convolution network based on emotional analysis towards mental health	2020	Zixiang Fe, Erfu Yang, David Da-Uei Li	Fully Connected Layer 6 of the AlexNet,Linear Discriminant Analysis Classifier (LDA)	97%	202 images of facial expressions were used from the JAFFE	These photos have been satisfactorily verified as a good training set for our network.

Emotion-based analysis of programming languages on Stack Overflow	2020	Stefano Cagnoni, Lorenzo Cozzini, Gianfranco Lombardo, Monica Mordonini, Agostino Poggi, Michele Tomaiuolo	Knowledge Discovery in Database process(KDD)	76%	Public posts datasets	In the future, examine responses and comments in addition to the original posts.
Sensing climate change and energy issues: Sentiment and emotion analysis with social media in the U.K. and Spain	2020	Maria L. Loureiro, Maria Allo	NRC Emotion Lexicon	High accuracy	Social media dataset from Twitter	Will take into account utilising deep learning approaches to fix these flaws

4. Dataset Implementation using LSTM

There have been many studies regarding the emotion analysis from the text. First identifying the method is needed and then identifying the dataset is required. We will use the LSTM method in our dataset. LSTM will have gates in which data is sent or thrown in a sequence. Voice synthesis, speech recognition, and text generation all can use LSTMs and GRUs. They can even be used to create video captions. LSTM is a type of RNN(recurrent neural network). Generally RNN is used for sequential data like text and audio. Typically, when creating an embedding matrix, i.e the calculations for each word's meaning (known as hidden states) are saved.

RNNs are unable to store all these calculations in their memory if, for example, a word is referenced 100 words into a text. RNNs are therefore unable to learn these long-term dependencies. So here comes the LSTM which can work well in such cases. LSTM works well with time series data.

4.1 Dataset

Amazon Book Review is the dataset where we have taken the reviews of the customer who have read a particular book and wrote the review. Initially the data is not pre-processed but afterwards we will pre-process the data and then load the dataset. The pre-processed dataset consists of 4 columns which are most important for identifying the emotion analysis. They are

- Unnamed 0: we will ignore this column
- rating: this column tells us the rating of the book
- reviewText: this column tells us the review that is given for the book
- summary: this column tells us about the summary of the book.

Here are the steps of implementing of the dataset

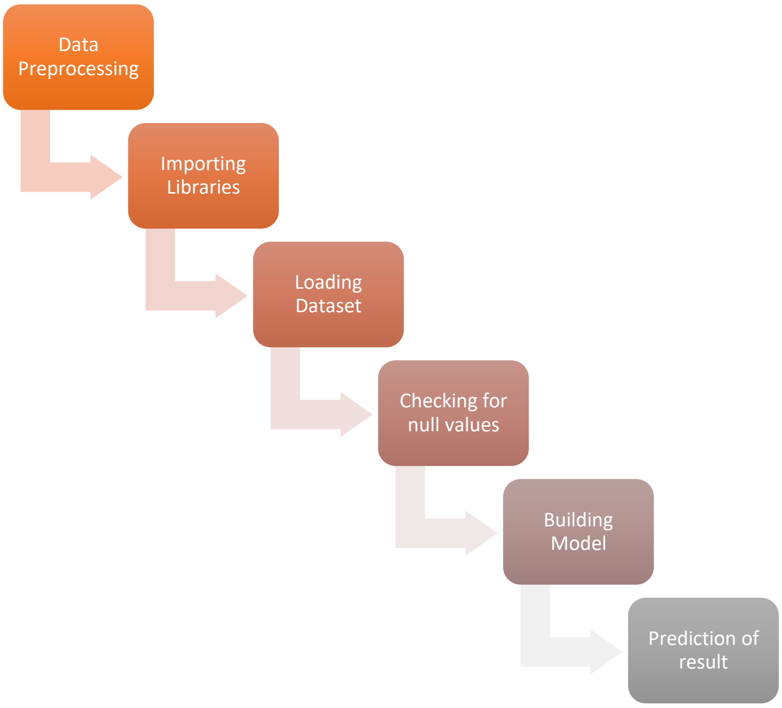

Figure 7. Implementation steps of the dataset

One regularization technique is dropout. To prevent over fitting, it is employed. We randomly remove some neurons as part of the dropout procedure. The likelihood of dropping the neurons is given as an argument to the layer, which accepts a number between 0 and 1. By doing so, over fitting is prevented and a robust model is produced.

The following graph shows the data of the model

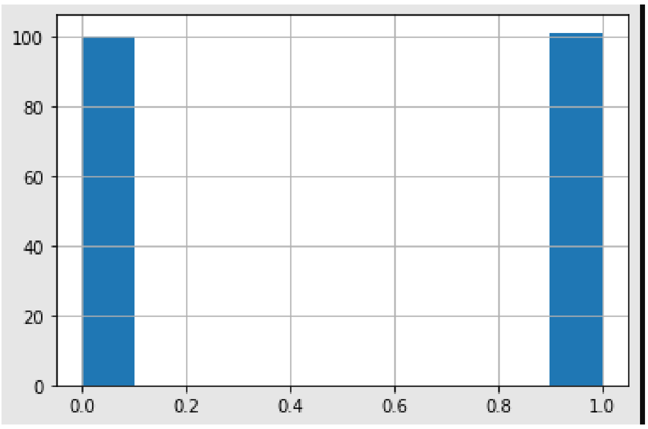

Figure 8. Data of the model

We will train and test the dataset. We got 90% accuracy on training set and 70% accuracy on test set. The following are the graphs we got by this model.

This graph shows the accuracy of the model.

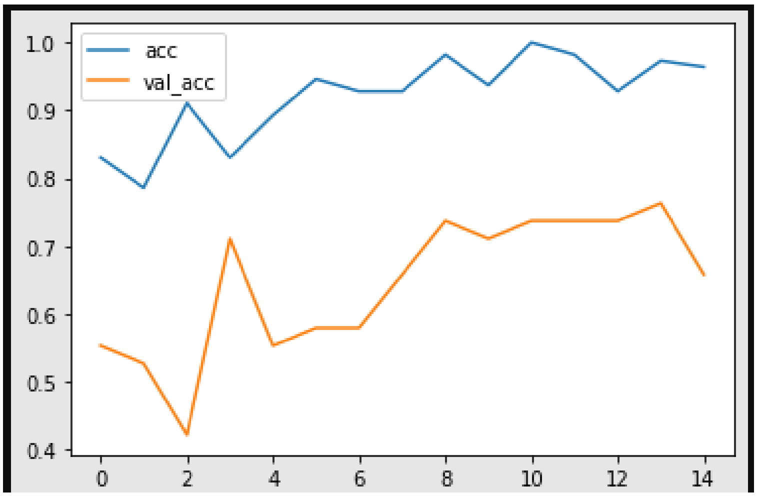

Figure 9: Accuracy graph of Dataset

This graph shows the loss of the model.

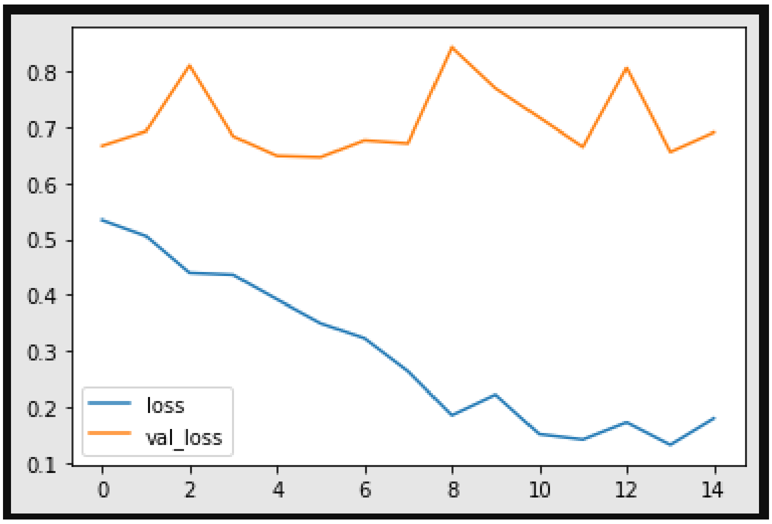

Figure 10: Loss of the model

Conclusion

After analysing the earlier works on the topic of emotion analysis, we come to the conclusion that significant work has already been done in the field, notably in the domain of textual datasets.

The experimentation results from some of the studies for various computational models, together with the overall system correctness of those models, are displayed in the table above. We notice that the system accuracy has greatly improved over time with the development or change of traditional computing approaches, the lexical resources, and the characteristics produced.

Future Work

We would like to use other approaches and implement the dataset and know the results and compared them with our work.

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