Literature Review

Student Name	**Atul Kumar Nayak**
Project Topic Title	**Emotion recognition from text and feedback analysis using deep learning**

1		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/9182441	Yanrong Zhang Jiayuan Sun Lingyue Meng Yan Liu	Sentiment analysis, tf-idf, sentiment dictionary, text similarity.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Proposed a sentiment analysis model for E-commerce Text Reviews by using sentiment dictionary.	Objective is to use sentiment dictionary-based method to mine e-commerce text reviews, and build a reverse sentiment dictionary for the problem that the same sentiment word has different sentiment polarities.	1. Extraction of Emotional Resources 2. Construction of emotion dictionary 3. Constructing reverse dictionary 4. Emotion analysis
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Pre-processing and part-of-speech tagging of the corpus.	Constructing a reverse emotion dictionary instead of just an emotion dictionary shows higher accuracy.	The results of part-of-speech tagging can be biased and need to be manually rectified.
2	TF-IDF algorithm is used to extract the keywords of the product. -TF algorithm counts the number of times a word appears in a comment. -The IDF algorithm counts how many comments a word exists in the corpus. -TF-IDF are calculated for all nouns, and the top 50 values are taken.	The method proposed in the paper accurately extracts evaluation objects from text reviews.	The accuracy rate of sentiment classification in the phone field using the proposed sentiment dictionary is lower compared to the computer field.
3	Extraction of Evaluation Objects -data is word-vectorized. -Similarity between the feature words (words in the review) and the keywords (extracted) is calculated using cosine similarity and the most similar feature word is taken as the evaluation object.	The paper proposes the construction of a domain specific emotion dictionary for computer and phone products.	
4	Extracting emotional resources by using parts of speech filtering and some specific rules.		

5	Construction of Benchmark Sentiment Dictionary -SO-PMI (Sentiment Orientation Pointwise Mutual Information) algorithm to determine the polarity of the words and store them in the dictionary. -It calculates the difference between the PMI between the word and the positive seed words and the PMI between the word and the negative seed words (seed word are frequent and have strong sentiment- positive or negative).		
6	Constructing reverse emotion dictionary -Maps sentiment words to their opposite sentiment.(Customer service-excellent-poor) -eg: high price and fast electricity consumption means negative sentiment even though high and fast are positive sentiments.		
7	Degree words are assigned with some weights.		
8	Overall sentiment of the comment is analysed.		

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Sentiment of the review	No. of negative words (N)		
	Weight of the degree words (D)		
	Emotional word (S=1 or -1)		

Relationship Among The Above 4 Variables in This article

Input and Output	Feature of This Solution	Contribution & The Value of This Work
	The solution builds its own sentiment dictionary for computers and phones, and the self-built sentiment dictionary shows better results than the public sentiment dictionary for sentiment classification.	Got to know how to build a domain specific sentiment dictionary for sentiment analysis and about a new approach of reverse sentiment dictionary for improved performance.

Input	Output
Text review of phone or computer	Sentiment of the review

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain

Reverse sentiment dictionaries are more robust to changes in language or domain than traditional sentiment dictionaries because they are not based on a fixed set of sentiment words.	It builds a domain specific emotion dictionary so it's not suitable to use for other domains.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The paper provides an approach for sentiment analysis by building a domain specific sentiment dictionary, and to overcome the problem of the same sentiment word having different sentiment polarities for different evaluation objects, it builds a reverse sentiment dictionary which shows better accuracy mainly for e-commerce text reviews.	HowNet sentiment dictionary, Accuracy	Abstract I. Introduction II. Status at home and abroad III. Related work IV. Sentiment Analysis V. Experimental Results and Analysis VI. Conclusion Acknowledgment References

Diagram/Flowchart

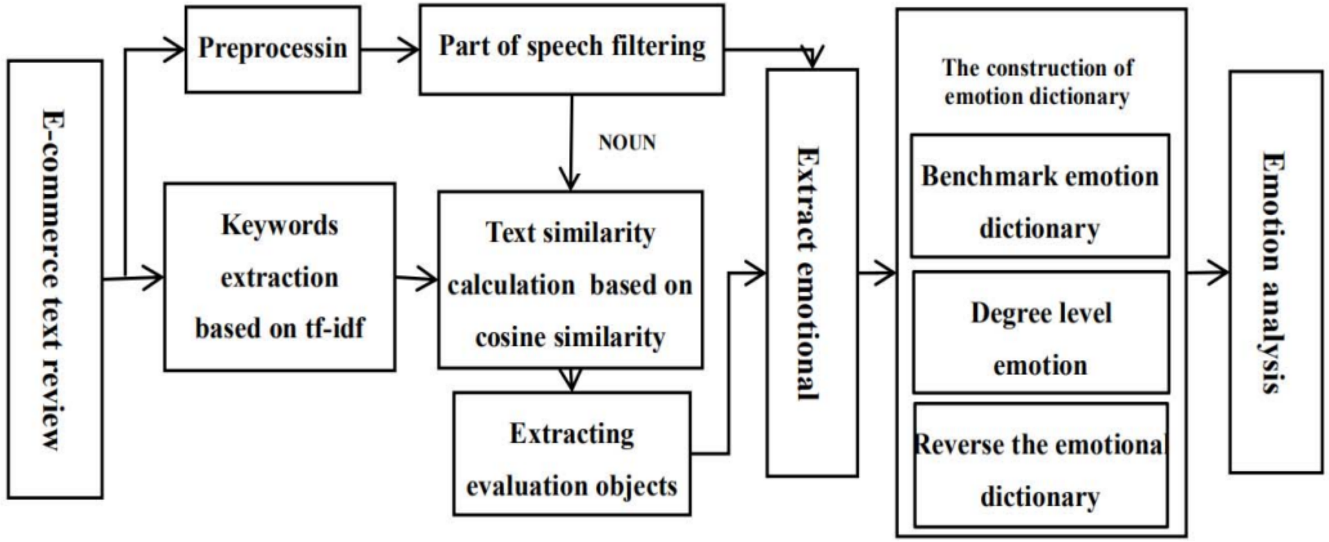

Fig. 1. E-commerce text review sentiment analysis roadmap

---End of Paper 1-

2		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/10212127	Ghamya Kotapati, Suma Kamalesh Gandhimathi, Palthiya Anantha Rao, Ganesh Karthik Muppagowni, K Ragha Bindu, M Sharath Chandra Reddy	Deep Learning, Natural language processing, Emotion Recognition, BERT (Bidirectional Encoder Representations for Transformers).
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
A Natural Language Processing for Sentiment Analysis from Text using Deep Learning Algorithm	Main objective is to understand the context of the sentence and categorize the sentence into the correct emotion.	Components of BERT model- CLS: added at the beginning of a text input, acts as a summary of the entire text. SEP: added at the end of a text input, helps to understand the relationships between the different sequences. Token embeddings: numerical representation of each token. Segment Embeddings: used to determine to which sentence the token belongs to. Sentence 1- index 0, sentence 2- index 1 Position embeddings: shows where a word's position is in a sentence. Hidden state: captures both the semantic and syntactic information of the token by considering all the embeddings. Classification layer: outputs the probabilities of the emotion category.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Pre-processing the text data.	BERT models are excellent at identifying context and interpreting sentiment within the context of the entire input text.	It only classifies the emotion into three categories i.e. positive, negative and neutral.
2	Tokenization is done to divide the text into separate words.	Record delicate emotions or mixed feelings, in addition to more complex sentiments.	
3	Encode the input data.		
4	Fine-tuning the BERT model.		
5	Testing model.		

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Accuracy	Fine tuning the model		

Relationship Among The Above 4 Variables in This article

Input and Output	Feature of This Solution	Contribution in This Work
(see table below)	The proposed model takes into account both the relationships between words and sentences and the overall context while determining the sentiment of the given input. It can also understand different degree of emotions.	Got to know how sentimental analysis can be used to monitor the movement of customer mood and feedback regarding a company's name, goods, and services.

Input	Output
Text from which sentiment needs to be recognized.	Analysed sentiment from the given text.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
BERT has proven to be very successful at tasks requiring natural language processing, specially it performs accurately for sentiment analysis tasks.	BERT models are computationally expensive to train and use. This can make them inaccessible for people with limited resources.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
BERT is trained on a huge text corpus, so the architecture or model is able to learn a variety of data patterns, comprehend language better, and effectively generalize and easily analyse the sentiment conveyed by the text.	Recall, precision and F1 score	Abstract I. Introduction II. Literature Survey III. Methodology IV. Results V. Conclusion VI. References

Diagram/Flowchart

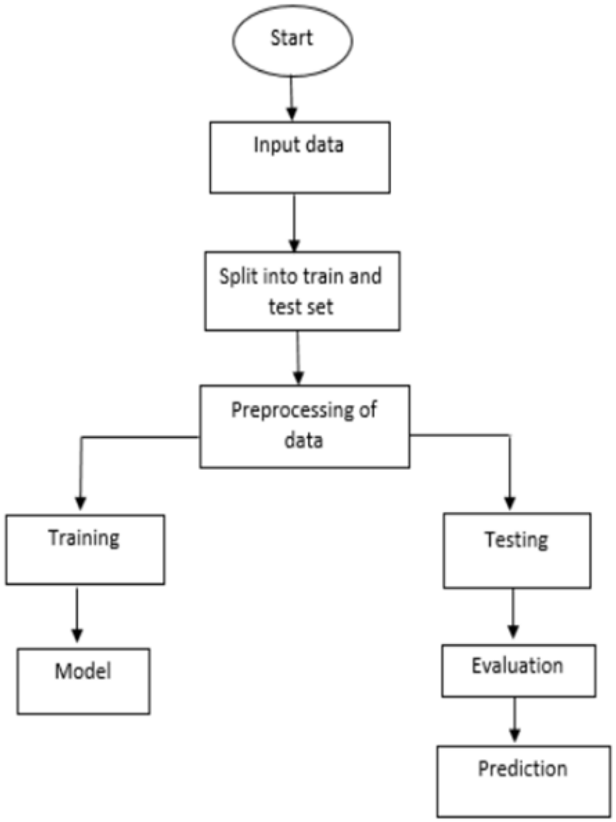

Figure 1.1 Block Diagram of Proposed Method

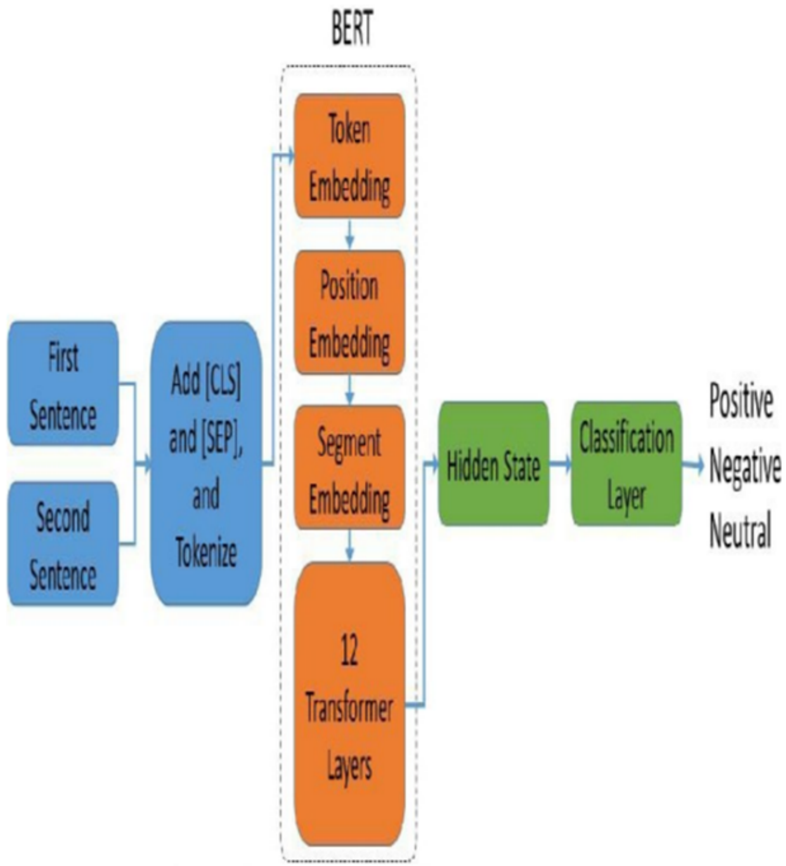

Figure 3.1 BERT Model

--End of Paper 2--

3		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/8769589	Aljoharah Almjawel Sahar Bayoumi Dalal Alshehri Soroor Alzahrani Munirah Alotaibi	Text Visualization, Tableau, Rstudio, Amazon Reviews, Opinion Analysis, Sentiment Analysis.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Sentiment Analysis and Visualization of Amazon Books' Reviews	The aim is to provide a practical way to visually analyze customer feedback sentiment using various visualization techniques.	1. Sentiment analysis 2. Visualization of reviews using different visualization techniques
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	The used dataset formed from two separate datasets (details of product description + details of review) and has 4 attributes- overall, summary, title and time of reviews.	Helps the customers to make decisions by giving review analysis to the customer.	The proposed model relies on a lexicon-based approach for sentiment analysis, which may lead to incorrect classifications of reviews especially for slang, colloquial, and jargon words.

2	Sentiment or qdap packages in R can be used for sentiment analysis, sentiment package requires installation of tm and Rstem packages. Tm-text preprocessing Rstem- stemming algorithms	The model enables users to compare sentiment reviews of different books with an interactive user interface.	The lexicon-based approach used in the model may not cover all opinion words as it's using a default sentiment dictionary, by creating a domain specific sentiment dictionary we can get more accurate results.
3	Several visualization techniques are used that helps users to visualize the information about different books.		
4	Packed bubbles: represent the frequency of positive, negative and neutral reviews of a book. Linear chart: represent the time when the reviews were written. Stacked bars: used to present the ratings of books and whether they are positive, neutral or negative. Word-cloud: it shows the book that has most reviews, and shows the most frequently used word in the reviews of books.		

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Review analysis	Rating		
	Summary		

	Title		
	Time of reviews		

Relationship Among The Above 4 Variables in This article

Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: Dataset of book reviews obtained from Amazon **Output**: Visual representation of the sentiment analysis results	Visualization of book reviews using 4 techniques allow users to- 1. Select a book and see if reviews are positive, neutral, or negative. 2. Get detailed information about a book of interest and compare the books.	The major contribution is the development of a visual approach for analyzing book reviews. Users can select specific books and determining the sentiment and rating of reviews.

Input	Output
Dataset of book reviews obtained from Amazon	Visual representation of the sentiment analysis results

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
It gives better analytical powers to the customers while buying a product. It also can be used by the product development unit for analysing their product.	Low accuracy in determining the correct sentiment of the reviews.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper

The proposed model has a dataset which includes 12 books reviews selected from Amazon, and contains 1000 records. This solution will help users to quickly and easily understand the overall sentiment of book reviews with visual analysis and find books of their interest.	Data Visualization- Tableau	Abstract I. Introduction II. Literature Review III. System Design IV. Results V. Conclusion VI. Future Work

Diagram/Flowchart

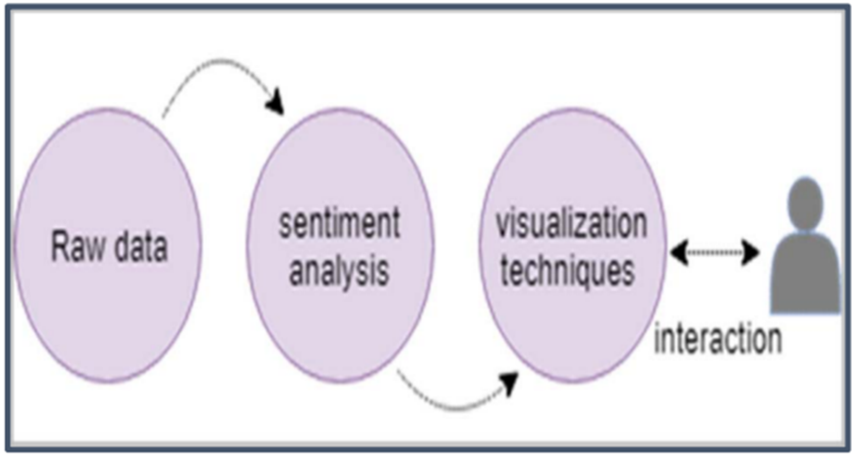

Figure.1. System Architecture

--End of Paper 3--

4		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/9792786	Raghavendra Reddy Ashwin Kumar U M	Sentiment Analysis, Opinion Mining, Convolutional Neural Network, Emoji and Social Network.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Proposed a multi-class sentiment analysis form text by using Enhanced Convolutional Neural Network (ECNN).	Objective is to find the emotion using text and emoji-based features.	1. Preprocessing the input text 2. Feature extraction 3. Identifying the correct emotion using ECNN 4. Comparing the model with different classification models

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	The dataset we used for this study is Amazon product reviews dataset with 10,000 tweets.	Can recognize the emotion in the text containing emojis which improves the accuracy.	Different OS has different types of emojis, this can make it difficult for the model to predict the emotion of a text that contains emojis, as the model may not be familiar with all of the emojis that are used.

2	Preprocessing techniques such as tokenization, stop-word removal, stemming, and lemmatization to clean the text data.		
3	The emotion of a sentence is analysed by dividing it into two parts. Emotion of the text is identified using an emotion dictionary and each emoji is replaced by its word meaning.		
4	The DeepEMoji model is fine tuned with e-commerce emoji and then used to extract sentiment and emotion features from the text and emojis in a tweet. These features are represented as a vector of numbers.		
5	The ECNN model then uses the features to classify the emotion of the text.		

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Recognized emotion	Set of words		
	Set of emojis		

Relationship Among The Above 4 Variables in This article

Input and Output	Feature of This Solution	Contribution & The Value of This Work
(see table below)	The model uses both text and emoji-based features to learn patterns in the data. This allows the model to recognize multiclass emotions.	Got to know how emojis can be used to classify the correct emotion of the given text.

Input	Output
Text from which emotion needs to be recognized.	Correct emotion of the given input text.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
ECNN with DeepEMoji gives better results than traditional classifiers like CNN, SVM, DT and NB.	Heavily rely on emojis for accurate classification.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The DeepEmoji model is fine tuned with features like emoji name, meaning, and review text using emoji-labeled texts from the E-commerce application for accurate classification of emotion from the reviews.	Accuracy, precision, recall and f-measure.	Abstract I. Introduction II. Related Work III. Methodology IV. Experimental Results V. Conclusion

Diagram/Flowchart

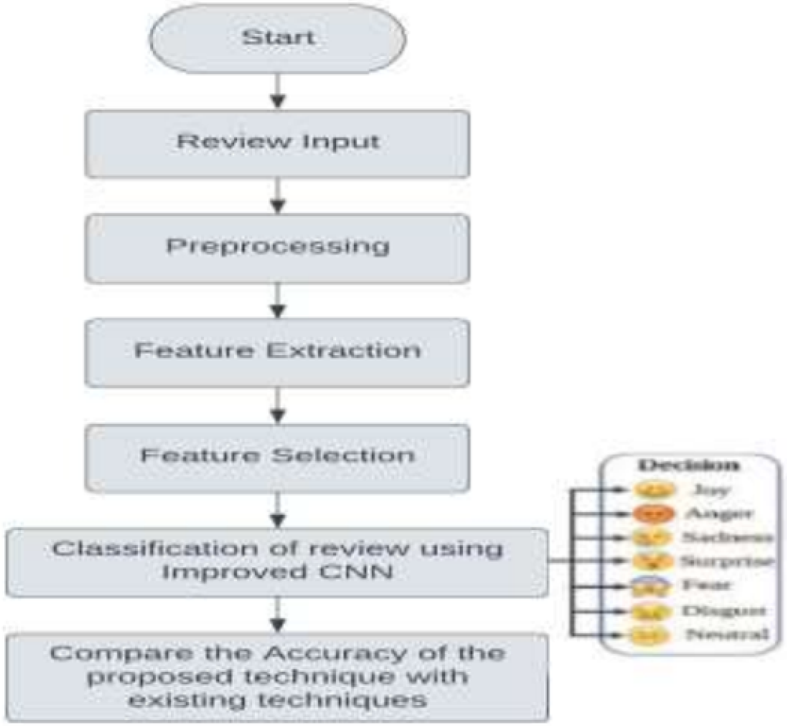

Fig. 1 Architecture of the proposed technique

--End of Paper 4—

5		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/9756494	Habib Izadkhah	Natural language processing (NLP), Deep learning, Convolutional neural network, Emotions.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Detection of multiple emotions in texts using a new deep convolutional neural network X-module.	The purpose of this paper is to detect multiple emotions in texts.	1. Creation of dataset 2. Creating customized X-module 3. Predicting multiple emotions from text
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Creation of multi-labeled dataset from CBET and semEval 18 datasets.	High accuracy in detecting multiple emotions from text.	It requires a large and balanced dataset of multi-labelled emotions, which may not be easily available or representative of real-world scenarios.
2	Preprocessing the raw data.	Created modified dataset for higher accuracy.	
3	Word embedding layer represent words as vectors of numbers using pre-trained word embedding models like FastText and GloVe.		

4	The Attention mechanism focus on the most important parts of an input sequence to understand the meaning of the sentence by softmax function (0-1)		
5	X-module is made up of R-blocks, X-modules are stacked upon each other and it performs emotion detection.		
6	R-blocks are made up of two 1-D CNN, and the output of the R-blocks are concatenated using filter concatenation and it widens the network.		
7	The fully connected layer gives the final output by using softmax activation function and produces probability of each emotion.		

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Multilabel Emotion	Text Data		

Relationship Among The Above 4 Variables in This article

Input and Output	Feature of This Solution	Contribution & The Value of This Work
(see Input/Output table below)	1. Existing systems tend to learn more single-emotion samples than multi-emotion samples in a dataset. 2. The number of texts from which only one emotion can be deduced is very small compared to texts from which more than one emotion can be deduced which reduces accuracy. But here a new dataset is created with multi label emotions.	1. Got to know that most of the datasets contain very less single emotion label which decreases their accuracy. 2. How 1-D CNN can be used for emotion detection.

Input	Output
Text to detect emotion	Vector of probabilities for each emotion class

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
Employing a wider network instead of just a deeper one, the solution overcomes existing architecture limitations such as computing overhead and overfitting.	Did not provide any possible solution to tackle the issue of single emotion label.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
1. It proposes a new deep convolutional neural network architecture, called X-module, that considers both the depth(layers) and width(filters) of the network, and uses identity connections, filter concatenation, and intermediate classifiers to improve the learning and performance of the model. 2. It uses attention mechanism to focus on the most important words in each text that contribute to the emotions	Jaccard index, Hamming Loss, micro-average precision and recall, F1-score.	Abstract I. Introduction II. Related Work III. Proposed Approach IV. Experimental Results V. Conclusion

3. Word embedding models (fast text and GloVe) convert into word vectors. 4. The intermediate classifiers are used in the X-module to prevent the "dying out" of the middle part of the network and to calculate the loss function, to improve the final loss function. 5. Identity Connection, connects the input to the output.		
Diagram/Flowchart		

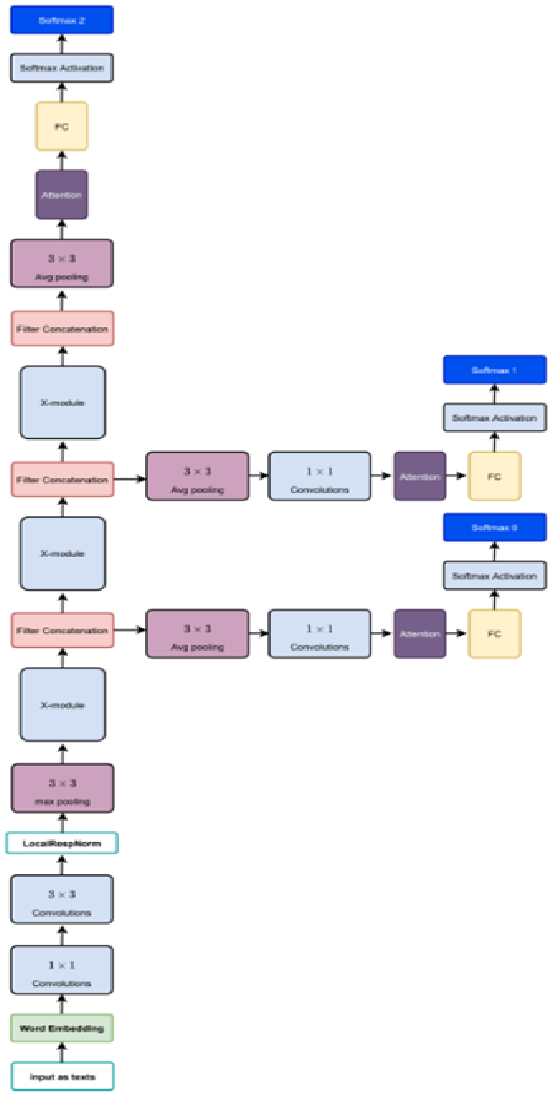

Fig. 3. The proposed architecture

Work Evaluation Table

<Use the same factors you have used in "Work Evaluation Table" to build your own "Proposed and Previous comparison table ">

	Work Goal	System's Components	System's Mechanism	Features /Characteristics	Cost	Speed	Security	Performance	Advantages	Limitations /Disadvantages	Platform	Results
Yanrong Zhang, Jiayuan Sun, Lingyue Meng, Yan Liu - 2020	sentiment dictionary-based method to mine e-commerce text reviews, and build a reverse sentiment dictionary for sentiment analysis.	-Extraction of Emotional Resources -Construction of emotion dictionary -Constructing reverse dictionary -Emotion analysis	-Sentiment dictionary -Reverse sentiment dictionary	Builds its own sentiment dictionary for computers and phones and shows better results.	-	-	-	The self-built sentiment dictionary performs better than public HowNet sentiment dictionary.	-Constructing a reverse emotion dictionary instead of just an emotion dictionary shows higher accuracy. -Domain specific sentiment dictionary.	-The results of part-of-speech tagging can be biased and need to be manually rectified. -Lower accuracy for mobile reviews.	Python	Computer sentiment - 89.2% Phone-84.3
Ghamya Kotapati, Suma Kamalesh Gandhimathi, Palthiya Anantha Rao,	Main objective is to understand the context of the sentence and categorize the	-CLS -SEP -Token embeddings	BERT	The proposed model takes into account both the relationships between	-	-	-	BoW, Naive Bayes, Support Vector Machines (SVM), or Random Forests has limited	-BERT models are excellent at identifying context and interpreting sentiment.	-It only classifies the emotion into three categories i.e. positive,	Python	Accuracy-95%

Ganesh Karthik Muppagowni, K Ragha Bindu, M Sharath Chandra Reddy - 2023	sentence into the correct emotion.	-Segment Embeddings -Position Embeddings -Hidden State -Classification layer		words and sentences and the overall context while determining the sentiment of the given input.				contextual understanding and BERT outperforms them.	-Different degree of emotions.	negative and neutral. -Computationally expensive.		
Aljoharah Almjawel, Sahar Bayoumi, Dalal Alshehri, Soroor Alzahrani, Munirah Alotaibi - 2019	The aim is to provide a practical way to visually analyze customer feedback sentiment using various visualization techniques.	-Sentiment analysis -Visualization	Lexical based approach- sentiment analysis Tableau- visualization	Get detailed information about a book of interest and compare the books.	-	-	-	Performs better for visual analysis of customer sentiment.	-Helps the customers to make decisions. -Interactive interface	lexicon-based approach for sentiment analysis is not efficient.	R, Tableau	Review analysis of a book
Raghavendra Reddy, Ashwin Kumar U M - 2022	Objective is to find the emotion using text and emoji-based features.	-Preprocessing the input text -Feature extraction	ECNN - with text and emoji based emotion recognition	The model uses both text and emoji-based features to learn	-	-	-	The proposed ECNN model performs better than CNN, SVM, DT and NB classifiers.	Can recognize the emotion in the text containing emojis which improves the accuracy.	Different OS has different types of emojis, this can make it difficult for the model to	Anaconda, python	accuracy- 90% precision- 83.5

		-Identifying the correct emotion using ECNN -Comparing the model with different classification models		patterns in the data. This allows the model to recognize multiclass emotions.						predict the emotion.		recall- 95% f-measure - 92%
Habib Izadkhah - 2022	The purpose of this paper is to detect multiple emotions in texts using X-module	-Creation of dataset -Creating customized X-module -Predicting multiple emotions from text	X-module using 1-D CNN	The number of texts from which only one emotion can be deduced is very small compared to texts from which more than one emotion can be deduced which reduces accuracy. But here a new dataset is created with multi label emotions.	-	-	-	CNN + GLOVE performs better	-High accuracy in detecting multiple emotions from text. -Created modified dataset for higher accuracy.	It requires a large and balanced dataset of multi-labelled emotions, which may not be easily available.	Python	Accuracy- 0.64663 Hamming Loss- 0.12864 micro F1- 0.72739 macro F1- 0.56238

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