

Literature Review (Secondary Research) Template

Student Name	k Midhilesh
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/abstract/document/8820254	Vikas Goel Amit Kr. Gupta Narendra Kumar	Sentiment Analysis NLP Opinion mining Deep learning Naïve Bayes RNN
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?
The paper proposes the use of machine learning techniques, specifically Recurrent Neural Networks (RNN) and Naive Bayes algorithm, for sentiment analysis of multilingual Twitter data.	The goal of the proposed solution for sentiment analysis of multilingual Twitter data is to classify the sentiments expressed in the tweets. The solution aims to solve the problem of analyzing and understanding the feelings and opinions of users expressed in different languages on Twitter.	Data Gathering Data Preprocessing Feature Extraction Sentiment Classification

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

sentiment (positive, negative, neutral) of the multilingual Twitter data		Features extracted from the tweets.		
Relationship Among The Above 4 Variables in This article				
Input and Output		Feature of This Solution	Contribution & The Value of This Work	
Input	Output	<ul style="list-style-type: none">• Comparison of the accuracy of RNN and Naive Bayes algorithms.• Analysis of efficiency, demonstrating that the RNN algorithm performs better than the Naive Bayes algorithm.• Dataset classification results, showing that RNN is more effective than Naive Bayes in terms of data analysis.• Use of machine learning algorithms for sentiment analysis.• Preprocessing of tweets to remove noise and filter out irrelevant data.	It addresses the problem of multilingual sentiment analysis, which is often overlooked in the field of natural language processing (NLP). The researchers highlight that most NLP models only support English language, making it impractical for analyzing sentiments in the thousands of other languages. This work proposes a solution by using Google Translator API to translate data into English and then applying classification algorithms like Naive Bayes (NB) and Recurrent Neural Network (RNN) for sentiment analysis.	
machine learning techniques, such as Recurrent Neural Networks (RNN) and Naive Bayes algorithm. These techniques are used to analyze the feelings expressed in different ways, such as negative, positive, favorable,	The output discussed in the paper for sentiment analysis of multilingual Twitter data is the classification of the tweets into different sentiment categories such as positive, negative, favorable, unfavorable, etc.			

unfavorable, thumbs up, thumbs down, etc		<ul style="list-style-type: none"> • Application of classification algorithms such as RNN and Naive Bayes. • Use of Google Translator API for multilingual data analysis. • Feature extraction through stemming and lemmatization. • Use of Core NLP Library and DotNet framework for natural language processing. 	
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
<p>The positive impact of this solution in the project domain is that it addresses the problem of multilingual sentiment analysis, which is rarely explored in research studies. By using the Google Translator API and the Core NLP Library, the solution allows for the analysis of sentiments in multiple languages. This is beneficial for organizations dealing with large amounts of data from different languages, as it enables them to extract useful information and gain insights from multilingual social media data.</p>		<p>Language Limitations</p> <p>Data Size and Complexity</p> <p>Unstructured and Unorganized Data</p> <p>Lack of Contextual Understanding</p> <p>Bias and Inaccuracy</p> <p>Need for Continuous Updates</p>	
Analyse This Work By Critical Thinking		The Tools That Assessed this Work	What is the Structure of this Paper
<ul style="list-style-type: none"> • The paper tackles an important real-world problem of analyzing sentiment from multilingual social media data. This has applications for marketing, public relations, politics etc. • The dataset size of 4000 labeled tweets is decent for training and testing the models. 		<p>Machine learning algorithms</p> <p>Dataset</p> <p>Evaluation metrics</p> <p>Comparative analysis</p> <p>Confusion matrices</p>	<p>Abstract</p> <p>Introduction</p> <p>Related Work</p> <p>Problem Statement and Data Formation</p> <p>Proposed Methodology</p>

<ul style="list-style-type: none">The authors use a sensible approach of translating non-English tweets to English using Google Translate before analysis. This allows handling diverse languages.	Visual graphs	Implementation Comparative Analysis Conclusion
Diagram/Flowchart		
 <pre>graph LR; A[Data Gathering] --> B[Google translator]; B --> C[Pre processing of Tweets]; C --> D[Feature Extraction]; D --> E[Apply Classification Algorithms]</pre>		

--End of Paper 1--

Reference in APA format		
URL of the Reference	Authors Names and Emails	Keywords in this Reference
https://ieeexplore.ieee.org/document/10007248	Reema Goyal Navneet Chaudhry Mandeep Singh	PocketSphinx Word2Vec Automated Speech Recognizer ISEAR Emotion detection
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?
<ul style="list-style-type: none"> • PocketSphinx for automated speech recognition • Word2Vec for text analysis • K-means clustering • TF-IDF vectorizer • Training and testing on the ISEAR emotion dataset 	The main goals are to create an emotion detection model that requires no labeled training data, works for low-resource languages, and can be personalized for individual users in an unsupervised manner. This solves key limitations of existing supervised models relying on labeled data and lexical resources.	PocketSphinx for ASR Word2Vec for text analysis K-means clustering on word vectors TF-IDF scoring Weighted sentiment scoring Emotion classification based on weighted sentiment and TF-IDF score

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

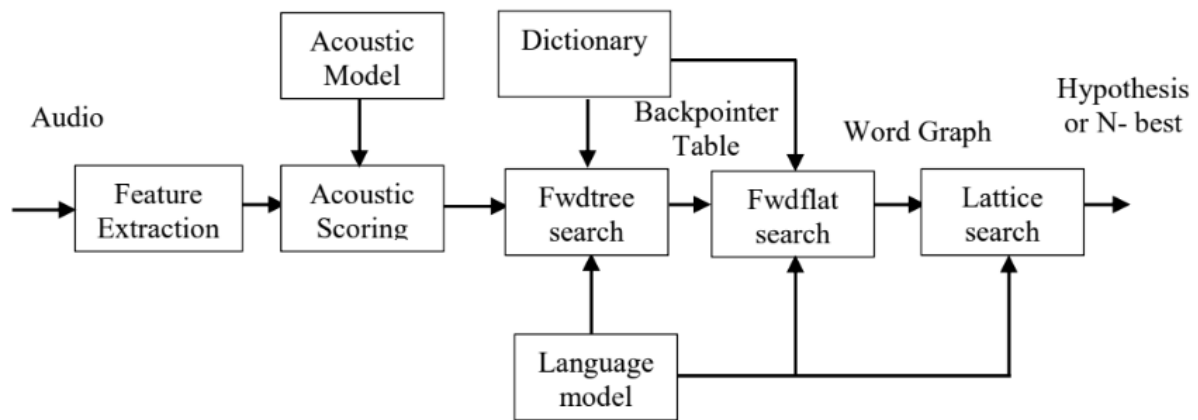
	Process Steps	Advantage	Disadvantage (Limitation)
1	Import data and preprocess data	importing and preprocessing data in the proposed model contribute to better data quality, improved model performance, increased accuracy, and efficient data handling.	
2	Pocketsphinx ASR	the use of Pocketsphinx ASR in the proposed model ensures accurate and real-time speech recognition, along with noise suppression and integration with a knowledge base.	
3	Word2Vec model	its ability to recognize similar words	High computational cost: Training word2vec can be computationally expensive for large datasets.
4	K-means Clustering	Handling large datasets	Determining the number of clusters
5	Tfidf weighing and emotion detection	Captures word importance Reduces the impact of common words	

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Emotion classification (positive, negative, neutral) predicted by the models	Features extracted from the text or speech input		

Relationship Among The Above 4 Variables in This article			
Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output	Emotion recognition using machine learning techniques Use of natural language processing techniques for semantic analysis and keyword extraction Utilization of the OCC model for connecting semantic analysis results to emotions Implementation of PocketSphinx for Automatic Speech Recognition (ASR)	The contribution of this work is the development of a customized emotion detection approach that aims to make the recognition process more realistic. The proposed model can classify human emotions extracted from speech signals or text. The authors utilize natural language processing techniques, machine learning algorithms, and deep learning approaches to estimate and classify emotions
The input of the proposed model described in the document can be either text or speech signals. If the input is in the form of speech signals, the model attempts to classify human emotions extracted from an Automated Speech Recognizer (ASR) along with text	The output of the proposed model is classification of emotions from text. The goal is to extend the emotion classification to cover all users' emotions as the dataset becomes stronger		

processing. If the input is text, it can be directly classified by the model			
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
it offers a customized emotion detection approach that makes the recognition process more realistic. By using a combination of speech signals and text processing, the model can accurately classify human emotions.		To mitigate these concerns, emotion detection systems should be carefully designed with ethical principles in mind, obtain user consent, ensure transparency, test for biases, and safeguard data privacy and security. Overall societal impacts should be considered, not just individual benefits. Ongoing oversight is needed as use cases expand over time.	
Analyse This Work By Critical Thinking	The Tools That Assessed this Work		What is the Structure of this Paper
Introduces a novel model for personalized emotion detection that cleverly combines NLP with speech processing. But further evaluation, ablation studies, comparative analysis, and discussion of limitations would significantly strengthen the paper and conclusions drawn. The critical analysis helps identify these areas for improvement while recognizing the innovative qualities demonstrated.	The tools used to assess this work include semantic analysis, case-based reasoning, natural language processing techniques, statistic-based parsing, dependency trees, emotion models, keyword-based techniques, supervised learning algorithms, unsupervised procedures, lexical resources, machine learning, deep learning algorithms, Pocket-sphinx (Automatic Speech Recognizer), Human Computer Interaction (HCI), linear support vector machine (Linear SVM), and ontologies such as Wordnet and Concept Net.		Introduction Proposed Model and Methodology Dataset Implementation Results Conclusions and Future Work
Diagram/Flowchart			



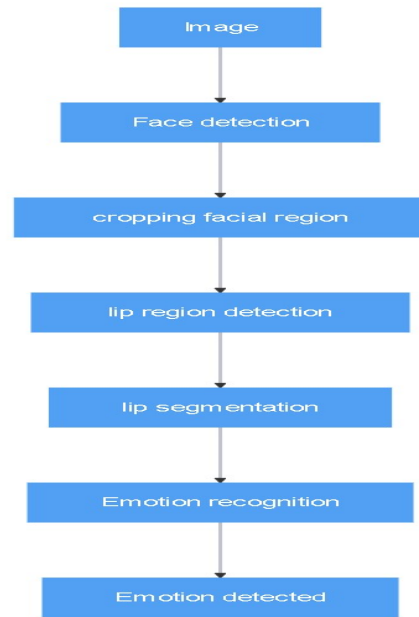
--End of Paper 2--

Reference in APA format			
URL of the Reference	Authors Names and Emails	Keywords in this Reference	
https://ieeexplore.ieee.org/document/9776385	Madhavi S. Darokar Dr. Atul D. Raut Dr. Vilas M. Thakre	Emotion Recognition, Social Network, Deep learning, Facial Expression.	
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 way to use the various AI and Machine learning tools that are available	The main goal is : 1. TO build a face detection model. 2. Extract features from face. 3. Built a layered Deep CNN and train it using face images and their features obtained from step 1 and Step 2.	SVM NEURAL NETWORK DEEP CNN JAFEE DATASET FACE DETECTION EMOTION RECOGNITION	
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 first step is Face detection and it is done by using various techniques. We use JAFFE dataset and C-means clustering algorithm	It gives better accurate outputs by analyzing the given data	System works well in front pose images only.
2	In the feature Extraction step we use techniques like Gabor Filter,Local Binary Pattern,SIFT.	Finds things at different sizes and angles Works even in changing lights	Needs a lot computer power Takes up lots of memory

			Used to be expensive
3	Emotion Classification	It achieves higher level of accuracy than the input data	Classifying emotions based on context is very challenging
Major Impact Factors in this Work			
Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Emotion classification predicted by the models	facial image features and encodings, as well as the labeled training datasets.		
Relationship Among The Above 4 Variables in This article			
Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output	Able to detect multiple emotions present within a single image by splitting using rule-based techniques.	This work explains the necessity of having a balanced dataset for emotion recognition in text. Got to know about the technique to achieve a balanced dataset.
Pictorial or in the form of emoji's data, extracted from social media and many other	The system is evaluated under the different parameters and is tested for the proper accuracy of		

sources is given as input.	output. It is also observed how the different objects in the image are classified and how accurately this classification is done.		
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
Deep neural networks for emotion recognition in social media can enable impactful new applications in mental health, marketing, education and more by providing scalable, accurate, and less biased models compared to existing approaches.		Overall, facial emotion recognition from social media photos needs to be pursued cautiously. Steps to mitigate risks include transparent development processes, testing for biases, consent-based data collection, studying psychological impacts, and securing models against malicious uses. Thoughtful governance and ethics review processes are critical.	
Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper	
This paper provides a reasonable high-level overview of facial emotion recognition and proposes using deep learning. However, the technical details and evaluation are lacking to convincingly demonstrate the merits of their approach. More rigorous experiments, details, and critical discussion would strengthen the paper. The ideas show promise but require further development and validation.	standard machine learning libraries like OpenCV, PyTorch, TensorFlow, Scikit-Learn etc. would likely provide the core tooling.	I.Introduction II.Background III.Previous Work Study IV.Existing Methodologies V.Analysis and Discussion VI.Proposed Framework	

		VII.Outcomes and Results VIII.Conclusion IX.Future Scope
Diagram/Flowchart		



—End of Paper 3—

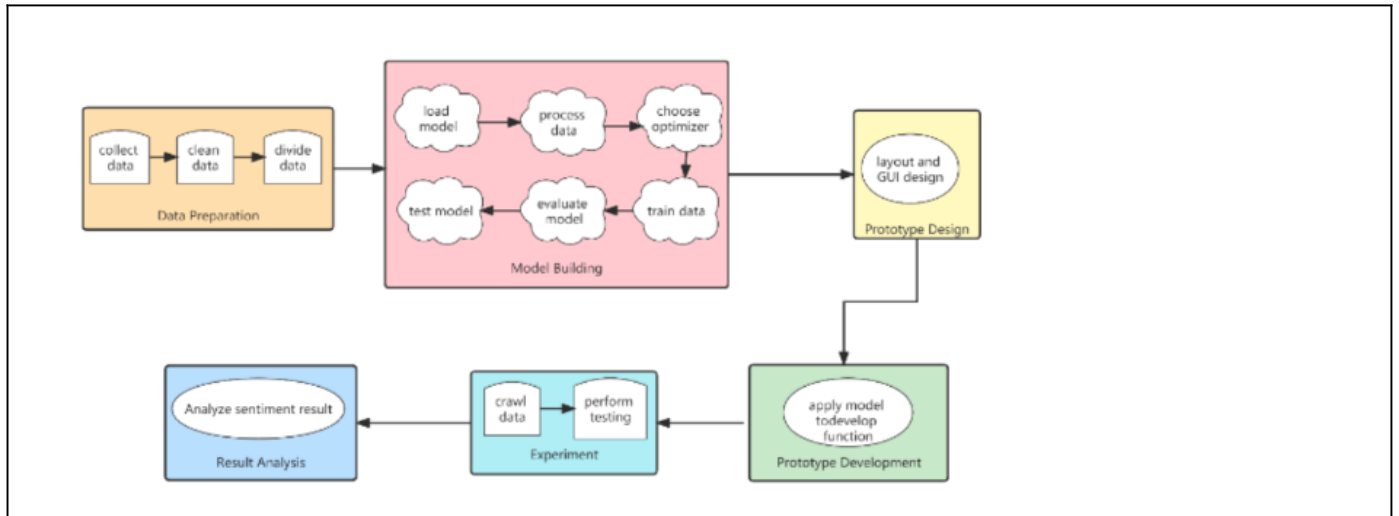
Reference in APA format		
URL of the Reference	Authors Names and Emails	Keywords in this Reference
https://ieeexplore.ieee.org/document/10194174	Yuxin Huang Shaidah Jusoh	Deep learning, Measurement, Sentiment analysis, social networking, text categorization, semantics, prototypes
The Name of the Current 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?
The current solution is an emotion and sentiment analysis prototype that has been developed using the ERNIE Tiny pre-trained model. It allows users to analyze single texts or process texts in batches. The prototype can classify emotions such as sadness, happiness, disgust, anger, like, surprise, and fear, as well as sentiment polarity such as positive, negative, and none.	<p>The goal of this solution is to develop a prototype for emotion and sentiment analysis of Chinese text. The prototype aims to assist individuals in analyzing and classifying emotions and sentiments in Chinese text, particularly in the context of social media and music platforms</p> <p>The problem that needs to be solved is the accurate classification and analysis of emotions and sentiments in Chinese text. The solution aims to address the limitations of existing methods by using a deep learning model called ERNIE Tiny, which is trained on a dataset of Chinese social media comments</p>	<p>User Interface Layout</p> <p>Single Text Function</p> <p>Batch Text Function</p> <p>Model Building</p> <p>Optimization Strategy and Train DataModel</p> <p>Evaluation and Prediction Testing</p> <p>Experiment</p>
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	METHODOLOGY	It provides a detailed plan that helps to keep researchers on track, making the process smooth, effective and manageable	
2	Model Building	The ability to create prototypes of products or structures before the final design is produced	The cost of a simulation model can be high
3	Optimization Strategy and Train Data	better results optimized time management	
4	Model Evaluation and Prediction Testing	advantage to predictive maintenance, such as being able to warn users of potential problems before they happen.	Increased cost and time consuming work.

Major Impact Factors in this Work			
Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Emotion classification predicted by the model	Text features extracted from the Chinese text data, which serve as input to the model		

Relationship Among The Above 4 Variables in This article		
Input and Output		Feature of This Solution
Input	Output	Contribution & The Value of This Work
study on emotion and sentiment classification for Chinese text	Research Framework and Methodology Prototype Development and User Interface Experiment and Result Analysis Conclusion and Future Work	Prototype Development Features Model Evaluation and Limitations: ERNIE Tiny Model and Interface: Experiment and Result Analysis Conclusion It focuses on emotion and sentiment classification for Chinese text. It introduces three main techniques for Chinese text emotion and sentiment analysis: emotion lexicon-based methods, traditional machine learning-based methods, and deep learning-based methods. The value for this work contributes to the field of Chinese text emotion and sentiment analysis by addressing the limitations of existing methods and exploring the use of deep learning approaches.

Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
The developed solution using the ERNIE Tiny model has a positive impact on emotion and sentiment classification in the project domain. It provides accurate sentiment detection, demonstrates the feasibility of sentiment detection from emotion classification, and offers potential for future enhancements.		There are several limitations and potential negative impacts that should be considered in the project domain. These include the limited consideration of punctuation symbols, the lack of comparison with other machine learning methods, the simplicity and limited functionality of the prototype, the lack of attractiveness in the user interface, and the scope limited to	
Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper	
adopts a sound methodology to address a novel problem combining emotion classification and sentiment analysis. More rigorous comparative evaluation and testing across diverse datasets would strengthen the conclusions and contributions. But within its scope, the work demonstrates promising initial results and capability of the proposed technique.	Critical thinking skills Technical knowledge Data analysis Data Collection and Cleaning Result Analysis	Introduction Related Work Methodology Prototype Implementation Result Analysis Conclusion	
Diagram/Flowchart			



—End of Paper 4—

Reference in APA format		
URL of the Reference	Authors Names and Emails	Keywords in this Reference
https://ieeexplore.ieee.org/document/10007248	Amal Shameem Ramesh babu Vigneshwaran Sundar Mrs. K. Veena	Machine Learning Emotion Detection NLP Learning
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?
The main technique explored is using machine learning, specifically classifiers like Support Vector Machines and Random Forests, to automatically detect and categorize emotions expressed in textual data. The article evaluates this ML-based text emotion detection approach and finds it provides improved accuracy over previous methods. The use of machine learning for emotion detection in text seems to be the core technique under investigation in this paper.	The key problem is accurately detecting emotional content in textual data, like social media posts, customer reviews, forums etc. The goal is to develop an effective machine learning approach for classifying text by emotions, showing it improves over previous techniques. Solving this would have benefits for applications like sentiment analysis, chatbots, and social media monitoring.	Data Collection: The abstract notes using blog posts for variety in writing style . Data Pre-Processing: The abstract mentions techniques like removing noise, converting case etc . Feature Extraction:.. This converts the text into numeric feature vectors. . Training and Test Sets: This provides data to train and evaluate the models . ML Models: Classification algorithms like Support Vector Machine, LinearSVC, and Random Forest

		<p>Classifier are used to train emotion detection models on the data.</p> <p>Model Evaluation: This validates the machine learning approach.</p> <p>Prediction: The best performing model is used to predict emotion categories for new text data.</p>
--	--	--

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	Data preprocessing	It improves accuracy and reliability	Duplicate data. Integrating data from different sources may result in redundant columns and rows in the data set.
2	Feature extraction	It can help to reduce the number of features without losing too much information.	
3	Train/test split	This allows you to get a general sense of how well your model is performing, and also tells you whether or not your model is performing as expected	Eliminating data that could have been used for training a machine learning model (testing data isn't used for training).
4	Model training and evaluation		Limited Scope

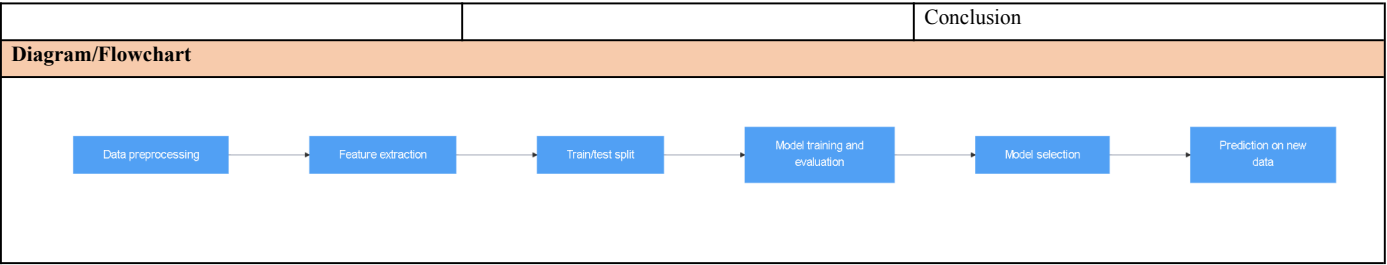
5	Model selection	The advantage of using a model is that it allows prediction and simplification of complex systems.	The disadvantage of a model is that they could be misleading and can be misinterpreted in a different way.
6	Prediction on new data		If the data used to train the model is incomplete, inaccurate, or biased, the model's predictions will also be flawed.
7	Application to real-world tasks	The advantages of apps include convenience, easy communication with customers, and online usage.	The disadvantages of apps include difficulty to create, the cost to create them, the cost to make them available to people, and the need for updates and support.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Emotion classification predicted by the machine learning models.	Testing data used to evaluate model performance		

Relationship Among The Above 4 Variables in This article

Input and Output		Feature of This Solution	Contribution & The Value of This Work			
<table><tr><th>Input</th><th>Output</th></tr><tr><td>The core input is the labeled text data used to train emotion detection models.</td><td>The output is the trained model that can categorize new text data into one of the predefined emotion classes.</td></tr></table>	Input	Output	The core input is the labeled text data used to train emotion detection models.	The output is the trained model that can categorize new text data into one of the predefined emotion classes.	<p>It uses machine learning algorithms such as logistic regression, K-NN classifier, and Adaboost classifier for text-based emotion detection.</p> <p>The proposed system investigates the effectiveness of Support Vector Classifier, LinearSVC, and RandomForestClassifier for identifying textual emotions.</p> <p>The system aims to improve the accuracy and effectiveness of emotion classification in text-based applications such as chatbots, customer support forums, and customer reviews</p>	<p>The key value is demonstrating a machine learning pipeline that provides state-of-the-art accuracy on a multiclass emotion detection task with real-world noisy text data. The comparative benchmarking and analysis is also a useful contribution. Overall, it helps advance the capability of systems to automatically understand emotional content in textual data.</p>
Input	Output					
The core input is the labeled text data used to train emotion detection models.	The output is the trained model that can categorize new text data into one of the predefined emotion classes.					
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain				
<p>This work helps advance emotion AI particularly for textual data, enabling more nuanced analysis of human emotions at scale across many applications from sentiment analytics to empathetic chatbots and beyond. More work is needed to realize the potential societal benefits and mitigate risks.</p>		<p>key risks relate to privacy, misuse potential, algorithmic bias, lack of transparency, limited accuracy, and the possibility of exacerbating or misjudging mental health conditions if applied recklessly.Ongoing research into improving robustness, avoiding bias, and enhancing transparency is important.</p>				
Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper				
<p>This work provides a solid foundation demonstrating the potential of ML for text emotion detection. Analyzing limitations and setting ethical guidelines should be priorities for future work. Thorough, critical evaluation is key to developing reliable and socially responsible emotion AI systems.</p>	<p>Data Processing Tools</p> <p>ML Tools</p> <p>Model Evaluation</p> <p>Coding Tools</p>	<p>Introduction</p> <p>Literature review</p> <p>Objective and problem statement</p> <p>Existing statement</p> <p>Proposed syatem</p>				



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
Vikas Goel Amit Kr. Gupta Narendra umar	Classify sentiments expressed in tweets into positive, negative, or neutral categories using machine learning techniques.	Data Gathering, Data Preprocessing, Feature Extraction, Sentiment Classification, Evaluation and Comparison	1. Data Gathering 2. Google Translator 3. Preprocessing of Tweets 4. Feature Extraction 5. Apply Classification Algorithms	Sentiment analysis of multilingual Twitter data, Used RNN and Naive Bayes algorithms, Google Translator API for multilingual data, NLP Library and .NET framework	-	-	-	RNN performs better than Naive Bayes in terms of data analysis and accuracy.	Addresses multilingual sentiment analysis, Use of machine learning algorithms, Preprocessing of tweets	Language limitations, Data size and complexity, Lack of contextual understanding, Bias and inaccuracy, Need for continuous updates	Python	Comparison of RNN and Naive Bayes algorithms, Dataset classification results
Reema Goyal, Navneet Chaudhry, Mandeep Singh	Create an emotion detection model that requires no labeled training data, works for low-resource languages, and can be personalized for individual users in an unsupervised manner.	PocketSphinx for ASR, Word2Vec for text analysis, K-means clustering, TF-IDF vectorizer	1. Import and preprocess data 2. PocketSphinx ASR 3. Word2Vec model 4. K-means clustering 5. TF-IDF weighting and emotion detection	Emotion recognition using machine learning, Natural language processing for semantic analysis, OCC model for mapping semantics to emotions, PocketSphinx for Automatic Speech Recognition	-	-	-	The paper proposes an unsupervised emotion detection approach combining PocketSphinx for speech recognition, Word2Vec for text analysis, K-means clustering, and TF-IDF weighting.	Customized emotion detection approach, Handles speech signals and text, Unsupervised and personalized	Privacy and security concerns, Potential biases, Need for oversight and ethical considerations	python	The key result is a customized emotion detection approach that works in an unsupervised manner, handles speech and text input, and can be personalized for users..
Madhavi S. Darokar, Dr. Atul D. Raut, Dr.		SVM, Neural Network, Deep CNN,	1. Face detection	Facial emotion recognition from social media, Use	-	-	-	Higher accuracy than input data	Detects multiple emotions in an	Works well only for front pose images, High	Python	Evaluates system parameters

Vilas M. Thakre	1. Build a face detection model 2. Extract features from faces 3. Build and train a layered Deep CNN using face images and features	JAFPE dataset, Face detection, Emotion recognition	using JAFPE dataset and C-means clustering 2. Feature extraction using Gabor Filter, Local Binary Pattern, SIFT 3. Emotion classification	of deep learning and neural networks, Ability to detect multiple emotions in an image					image, Explains need for balanced dataset	computational requirements, Challenging to classify emotions based on context		and classification accuracy
Yuxin Huang, Shaidah Jusoh	Develop a prototype for emotion and sentiment analysis of Chinese text to assist in classifying emotions and sentiments, particularly in social media and music platforms	User Interface Layout, Single Text Function, Batch Text Function, Model Building, Optimization Strategy and Train Data, Model Evaluation and Prediction Testing, Experiment	1. Methodology 2. Model Building 3. Optimization Strategy and Train Data 4. Model Evaluation and Prediction Testing	Emotion and sentiment classification for Chinese text, Use of ERNIE Tiny pre-trained model, Classifies emotions like sadness, happiness, anger, etc., Classifies sentiment polarity like positive, negative, none				The paper develops a prototype system using the ERNIE Tiny pre-trained model for emotion and sentiment analysis of Chinese text. The prototype can classify emotions and sentiment polarity, suggesting it is capable of performing the intended tasks to some degree.	Addresses limitations of existing methods, Explores deep learning approaches, Develops a working prototype	: Limited consideration of punctuation, Lack of comparison with other ML methods, Simple and limited prototype functionality, Unattractive user interface, Limited scope to Chinese text	Python	Prototype development, Model evaluation, Experiment and result analysis
Amal Shameem, Ramesh babu, Vigneshwar	Develop an effective machine learning approach for	Data Collection, Data Preprocessing, Feature	1. Data preprocessing 2. Feature extraction	Machine learning for text-based emotion detection, Use of algorithms like				Improved accuracy compared to previous techniques	Effective for multiclass emotion detection, Comparative	Limited scope, Potential for bias and inaccuracy, Lack of transparency,	Python	Benchmarks accuracy of different models on

an, Sundar, Mrs. K. Veena	classifying text by emotions, showing improvement over previous techniques	Extraction, Training and Test Sets, ML Models (SVM, LinearSVC, Random Forest), Model Evaluation, Prediction	3. Train/test split 4. Model training and evaluation 5. Model selection 6. Prediction on new data 7. Application to real-world tasks	SVM, LinearSVC, Random Forest, Evaluation on noisy real-world text data					benchmarking and analysis, Advances capability for understanding emotions in text	Privacy concerns, Risks of misuse and misdiagnosis		emotion detection task
----------------------------------	--	---	--	---	--	--	--	--	---	--	--	------------------------