

Department of Computer Science and Engineering
Bangladesh University of Business and Technology (BUBT)



CSE 498: Literature Review Records

Student's Id and Name	Name: Md Sabbir Ahmed ID:19202103187
Project Title	Emotion Detection for Bangla language
Course Teacher's Name & Designation	Name: Khan Md. Hasib & Designation: Assistant Professor, Department of CSE, BUBT

Person 03

Aspects	Paper # 1 (Title)															
Title / Question (What is problem statement?)	Emotion Detection from Bangla Text Corpus Using Naïve Bayes Classifier.															
Objectives / Goal (What is looking for?)	The purpose of this paper is to figure out how to detect different kinds of emotions from Banglian text using a NB classifier and other features like stemmer, POS tagger, ngrams, and TF-IDF. This paper is going to look at how emotion detection works in Banglian, which is still a work in progress, and how to analyze human emotions from text data.															
Methodology / Theory (How to find the solution?)	<p>The paper uses a Multinomial Naïve Bayes (NB) classifier for emotion detection from Bangla text. Various features are used in conjunction with the NB classifier, including stemmer, parts-of-speech (POS) tagger, n-grams, and term frequency-inverse document frequency (tf-idf)</p> <ul style="list-style-type: none"> . The dataset is divided into training and test data, and both undergo pre-processing steps and feature selection techniques before being fed into the classifier . The Multinomial NB classifier, implemented using scikit-learn, is used for predicting emotions from the text . The classifier calculates the class probability using the Bayesian theorem and selects the class with the maximum probability as the most probable class for a document . The overall accuracy of the final model in classifying text into three emotion classes (happy, sad, and angry) is 78.6. 															
Software Tools (What program/software is used for design, coding and simulation?)	Python Language and library															
Simulation/Test Data (What parameters are determined?)	<div>TABLE I. CLASS DISTRIBUTION IN THE DATASET</div> <table> <tr> <th>Label</th> <th>Training Set</th> <th>Test Set</th> </tr> <tr> <td>Happy</td> <td>1582</td> <td>230</td> </tr> <tr> <td>Sad</td> <td>1062</td> <td>104</td> </tr> <tr> <td>Angry</td> <td>1136</td> <td>86</td> </tr> <tr> <td>Total</td> <td>3780</td> <td>420</td> </tr> </table>	Label	Training Set	Test Set	Happy	1582	230	Sad	1062	104	Angry	1136	86	Total	3780	420
Label	Training Set	Test Set														
Happy	1582	230														
Sad	1062	104														
Angry	1136	86														
Total	3780	420														

Result / Conclusion (What was the final result?)	The paper found that using a NB classifier and various features, the proposed method of detecting emotions from Bangla text was accurate by 78.6 when it came to classifying them into three categories: happy, sad and angry.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	Not mentioned
Terminology (List the common basic words frequently used in this research field)	Emotion Detection, Machine Learning, Natural Language Processing, Bangla Text Processing, Naïve Bayes.
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	This paper related to Our research paper so, we can use huge amount of dataset and get a better accuracy .

Aspects	Paper # 2 (Title)
Title / Question (What is problem statement?)	A Systematic Review of Sentiment Analysis from Bengali Text using NLP
Objectives / Goal (What is looking for?)	The purpose of this review paper is to conduct a systematic review of sentiment analysis in Bengali (SA) and present a series of relatively good research papers in the field. The purpose of the review paper is to present the current methods of sentiment analysis in Bengal, highlight the preliminary steps, characteristics, scope of improvement, and evaluate the performance of sentiment analysis in the Bengali language. The aim of the review is to recognize the shortcomings of the current research methods in Bengal sentiment analysis and suggest improvements for improved performance.
Methodology / Theory (How to find the solution?)	The researchers conducted a systematic literature review following the guidelines for a systematic review . They used a manual search procedure to obtain answers to their research questions from specific sources . The researchers proposed to use the Analytic Hierarchy Process (AHP) weighted Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method to prioritize the papers . They created a decision matrix with alternative papers and attributes such as Accuracy, Sentiment Category, Size, and Sensitivity Noise . To evaluate the sentiment analysis models, the researchers reviewed different papers that used various techniques such as LR, DT, RF, MNB, KNN, SVM, and stochastic gradient descent (SGD) algorithm . They also considered lexicon dictionary-based approaches, sentiment scoring, and backtracking algorithms for sentiment analysis in Bengali text
Software Tools (What program/software is used for design, coding and simulation?)	python and python library

Simulation/Test Data (What parameters are determined?)	<table><caption>Table 1: Summary of the research</caption><thead><tr><th>Author name</th><th>Method</th><th>Year</th><th>E-library</th></tr></thead><tbody><tr><td>Shakil <i>et al.</i></td><td>NB</td><td>2019</td><td>IEEE</td></tr><tr><td>Parash <i>et al.</i></td><td>NB, DT</td><td>2018</td><td>IEEE</td></tr><tr><td>Tahsiron de Khan</td><td>RF</td><td>2019</td><td>IEEE</td></tr><tr><td>Tajmro de Ali</td><td>LSTM, CNN</td><td>2018</td><td>IEEE</td></tr><tr><td>Nahs <i>et al.</i></td><td>TF-IDF</td><td>2018</td><td>JICA</td></tr><tr><td>Chowdhury de Chowdhury</td><td>SVM, NaïveBay</td><td>2018</td><td>IEEE</td></tr><tr><td>Aziz <i>et al.</i></td><td>RNN</td><td>2018</td><td>E. Gate</td></tr><tr><td>Tahsin <i>et al.</i></td><td>NB</td><td>2019</td><td>IEEE</td></tr><tr><td>Sakhas de Bhattacharya</td><td>NB</td><td>2017</td><td>IEEE</td></tr><tr><td>Shamshi <i>et al.</i></td><td>SVM, TF-IDF</td><td>2018</td><td>IEEE</td></tr><tr><td>Alam <i>et al.</i></td><td>CNN</td><td>2017</td><td>IEEE</td></tr><tr><td>Dar de Sathas</td><td>Lexicon</td><td>2019</td><td>IEEE</td></tr><tr><td>Ebrahim <i>et al.</i></td><td>NB</td><td></td><td></td></tr><tr><td>Tajmro <i>et al.</i></td><td>NaïveBay</td><td>2019</td><td>IEEE</td></tr><tr><td>Tahsin <i>et al.</i></td><td>NB</td><td>2018</td><td>E. Gate</td></tr><tr><td>Tamim <i>et al.</i></td><td>MBN</td><td>2019</td><td>ACM</td></tr><tr><td>Chowdhury <i>et al.</i></td><td>BERT</td><td>2020</td><td>IEEE</td></tr><tr><td>Al-Amin <i>et al.</i></td><td>CNN, SG</td><td>2017</td><td>IEEE</td></tr><tr><td>Aziz <i>et al.</i></td><td>LSTM</td><td>2018</td><td>E. Gate</td></tr><tr><td>Saad de Jayaraman</td><td>RR, SVM, LR, RF</td><td>2019</td><td>IEEE</td></tr></tbody></table>	Author name	Method	Year	E-library	Shakil <i>et al.</i>	NB	2019	IEEE	Parash <i>et al.</i>	NB, DT	2018	IEEE	Tahsiron de Khan	RF	2019	IEEE	Tajmro de Ali	LSTM, CNN	2018	IEEE	Nahs <i>et al.</i>	TF-IDF	2018	JICA	Chowdhury de Chowdhury	SVM, NaïveBay	2018	IEEE	Aziz <i>et al.</i>	RNN	2018	E. Gate	Tahsin <i>et al.</i>	NB	2019	IEEE	Sakhas de Bhattacharya	NB	2017	IEEE	Shamshi <i>et al.</i>	SVM, TF-IDF	2018	IEEE	Alam <i>et al.</i>	CNN	2017	IEEE	Dar de Sathas	Lexicon	2019	IEEE	Ebrahim <i>et al.</i>	NB			Tajmro <i>et al.</i>	NaïveBay	2019	IEEE	Tahsin <i>et al.</i>	NB	2018	E. Gate	Tamim <i>et al.</i>	MBN	2019	ACM	Chowdhury <i>et al.</i>	BERT	2020	IEEE	Al-Amin <i>et al.</i>	CNN, SG	2017	IEEE	Aziz <i>et al.</i>	LSTM	2018	E. Gate	Saad de Jayaraman	RR, SVM, LR, RF	2019	IEEE
Author name	Method	Year	E-library																																																																																		
Shakil <i>et al.</i>	NB	2019	IEEE																																																																																		
Parash <i>et al.</i>	NB, DT	2018	IEEE																																																																																		
Tahsiron de Khan	RF	2019	IEEE																																																																																		
Tajmro de Ali	LSTM, CNN	2018	IEEE																																																																																		
Nahs <i>et al.</i>	TF-IDF	2018	JICA																																																																																		
Chowdhury de Chowdhury	SVM, NaïveBay	2018	IEEE																																																																																		
Aziz <i>et al.</i>	RNN	2018	E. Gate																																																																																		
Tahsin <i>et al.</i>	NB	2019	IEEE																																																																																		
Sakhas de Bhattacharya	NB	2017	IEEE																																																																																		
Shamshi <i>et al.</i>	SVM, TF-IDF	2018	IEEE																																																																																		
Alam <i>et al.</i>	CNN	2017	IEEE																																																																																		
Dar de Sathas	Lexicon	2019	IEEE																																																																																		
Ebrahim <i>et al.</i>	NB																																																																																				
Tajmro <i>et al.</i>	NaïveBay	2019	IEEE																																																																																		
Tahsin <i>et al.</i>	NB	2018	E. Gate																																																																																		
Tamim <i>et al.</i>	MBN	2019	ACM																																																																																		
Chowdhury <i>et al.</i>	BERT	2020	IEEE																																																																																		
Al-Amin <i>et al.</i>	CNN, SG	2017	IEEE																																																																																		
Aziz <i>et al.</i>	LSTM	2018	E. Gate																																																																																		
Saad de Jayaraman	RR, SVM, LR, RF	2019	IEEE																																																																																		
Result / Conclusion (What was the final result?)	The authors use the TOPSIS method to create a sequence of comparatively better research papers on sentiment analysis in Bengali.																																																																																				
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	<p>Complexity of the Bengali language and limited online presence of Bengali language content pose challenges in sentiment analysis in Bengali text.</p> <p>Automatic sentiment analysis systems face difficulties in detecting sentiment in sentences where there is no strongly positive or negative sense, or when multiple entities in a sentence have different sentiments.</p> <p>Conventional methods of sentiment analysis have limitations in terms of handling slang, incorrect spellings, and the need for language-specific resources like WorldNet and sentiwordNet for Bengali.</p> <p>Negative words in Bengali can express different sentiments depending on the context, making it challenging for automatic sentiment analysis systems.</p> <p>Comparing different famous or infamous people or objects in a sentence can be difficult for sentiment analysis systems to determine the sentiment accurately.</p> <p>There is a need for research on article-level sentiment analysis in Bengali, as most existing research focuses on sentence-level sentiment analysis.</p>																																																																																				
Terminology (List the common basic words frequently used in this research field)	Bangla, NLP, Review, Sentiment, Survey																																																																																				
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	we can use TOPSIS method in our research project to get a better accuracy.																																																																																				

Aspects	Paper # 3 (Title)																																																				
Title / Question (What is problem statement?)	Hyper-Tuned Convolutional Neural Networks for Authorship Verification in Digital Forensic Investigations																																																				
Objectives / Goal (What is looking for?)	Researchers want to see if hypertuning can help make CNNs more accurate for authorship verification in digital forensics. We'll be using a hypertuned version of the CNN model and three well-known optimization algorithms. The aim is to prove that the optimization algorithm plays a big role in how well the CNN works for authorship verification. This could be helpful for things like figuring out who wrote an anonymous threat or how to spot plagiarism.																																																				
Methodology / Theory (How to find the solution?)	This paper looks at how to run experiments to verify authorship in digital forensic investigations using a hyper-tuned CNN model and three popular optimization algorithms. It uses a dataset of 1200 samples, each with 100 samples for one author, and includes a variety of writing styles to make sure the scenario is realistic. The text samples are collected from handwritten Urdu text and scanned and digitized before being fed into the CNN model. The input data is converted to a numerical representation with word embeddings and then fed into a convolutional layer to extract features. The output is flattened, flattened again, and passed through a full connected layer to map out the extracted features to the potential authors. To avoid overfitting, dropout regularization, batch normalization, and better training stability and speed are used. The performance of the model is evaluated by comparing the performance of three optimization algorithms.																																																				
Software Tools (What program/software is used for design, coding and simulation?)	Python language and library																																																				
Simulation/Test Data (What parameters are determined?)	<div>Table 2: The details of the dataset</div> <table><tr><th>Author ID</th><th>Number of samples</th><th>Age range</th><th>Gender</th></tr><tr><td>1</td><td>100</td><td>25-30</td><td>Male</td></tr><tr><td>2</td><td>100</td><td>20-25</td><td>Female</td></tr><tr><td>3</td><td>100</td><td>30-35</td><td>Male</td></tr><tr><td>4</td><td>100</td><td>20-25</td><td>Female</td></tr><tr><td>5</td><td>100</td><td>25-30</td><td>Male</td></tr><tr><td>6</td><td>100</td><td>35-40</td><td>Female</td></tr><tr><td>7</td><td>100</td><td>20-25</td><td>Male</td></tr><tr><td>8</td><td>100</td><td>30-35</td><td>Female</td></tr><tr><td>9</td><td>100</td><td>25-30</td><td>Male</td></tr><tr><td>10</td><td>100</td><td>20-25</td><td>Female</td></tr><tr><td>11</td><td>100</td><td>30-35</td><td>Male</td></tr><tr><td>12</td><td>100</td><td>25-30</td><td>Female</td></tr></table>	Author ID	Number of samples	Age range	Gender	1	100	25-30	Male	2	100	20-25	Female	3	100	30-35	Male	4	100	20-25	Female	5	100	25-30	Male	6	100	35-40	Female	7	100	20-25	Male	8	100	30-35	Female	9	100	25-30	Male	10	100	20-25	Female	11	100	30-35	Male	12	100	25-30	Female
Author ID	Number of samples	Age range	Gender																																																		
1	100	25-30	Male																																																		
2	100	20-25	Female																																																		
3	100	30-35	Male																																																		
4	100	20-25	Female																																																		
5	100	25-30	Male																																																		
6	100	35-40	Female																																																		
7	100	20-25	Male																																																		
8	100	30-35	Female																																																		
9	100	25-30	Male																																																		
10	100	20-25	Female																																																		
11	100	30-35	Male																																																		
12	100	25-30	Female																																																		
Result / Conclusion (What was the final result?)	This hyper-tuned CNN model was the best for authorship verification in digital forensic investigations, with accuracy up to 90.00.																																																				
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	Not mentioned																																																				
Terminology (List the common basic words frequently used in this research field)	Convolutional Neural Network (CNN); hyper-tuning; authorship verification; digital forensics.																																																				

Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)																			
Aspects	Paper # 4 (Title)																		
Title / Question (What is problem statement?)	Automatic emotion detection in text streams by analyzing Twitter data																		
Objectives / Goal (What is looking for?)	This paper is all about how to use machine learning to detect emotions in text streams. We'll be looking at analyzing Twitter data to figure out the best way to do this. We'll also be looking at the challenges of automatic emotion detection, like the fact that emotions are subjective and different people have different ways of expressing them and perceiving them. We'll be proposing a way to use affect to define classes of emotions, as well as a soft classification method to figure out how likely it is that a message will be assigned to a certain emotion class. Plus, we'll be showing an online method for measuring public emotion and detecting emotional bursts in text streams.																		
Methodology / Theory (How to find the solution?)	Paper uses dimensional affect model for emotions. Soft classification used to assign multiple emotions to messages. Supervised learning system for emotion classification, with offline training. Introduces EmotexStream for real-time emotion tracking. Proposes online method for public emotion measurement. Evaluates accuracy of hashtags as emotion labels. Conducts user studies with experts and novices for validation.																		
Software Tools (What program/software is used for design, coding and simulation?)	Python and Library																		
Simulation/Test Data (What parameters are determined?)	<div>Table 1 Number of tweets collected as labeled data</div> <table><tr><th>Class</th><th>Happy-Active</th><th>Happy-Inactive</th><th>Unhappy-Active</th><th>Unhappy-Inactive</th><th>Total</th></tr><tr><td>#Tweets before preprocessing</td><td>40,000</td><td>41,000</td><td>44,000</td><td>41,000</td><td>166,000</td></tr><tr><td>#Tweets after preprocessing</td><td>34,000</td><td>30,000</td><td>37,000</td><td>34,000</td><td>13,5000</td></tr></table>	Class	Happy-Active	Happy-Inactive	Unhappy-Active	Unhappy-Inactive	Total	#Tweets before preprocessing	40,000	41,000	44,000	41,000	166,000	#Tweets after preprocessing	34,000	30,000	37,000	34,000	13,5000
Class	Happy-Active	Happy-Inactive	Unhappy-Active	Unhappy-Inactive	Total														
#Tweets before preprocessing	40,000	41,000	44,000	41,000	166,000														
#Tweets after preprocessing	34,000	30,000	37,000	34,000	13,5000														

Result / Conclusion (What was the final result?)	The authors have come up with a way to automatically detect emotions in text messages using a supervised learning system. They've created models to classify emotions in text messages and created a two-step framework, EmotexStream, to track emotions in real-time. The experiments have shown that the models correctly classify emotions in 90.00 of texts, and EmotexStream is great for classifying live streams of tweets. They've also come up with an online method for measuring public emotion and detecting emotional-intensive moments in text messages. Plus, they've done user studies with psychology experts and beginners to see how accurate hashtags are as emotion labels.
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	Emotions are subjective concepts with fuzzy boundaries and variations in expression and perception, making automated emotion detection a major challenge Analyzing text in real-time is challenging due to the noise and fast-paced nature of tweets in the wild . Tweets containing negated phrases like "not sad" or "not happy" pose a challenge as they may convey the opposite emotion than indicated by the words alone . The presence of noise in text streams can affect the accuracy of emotion detection, as it may introduce irrelevant or misleading information . The selection of appropriate features and classifiers for emotion detection is crucial for achieving accurate results
Terminology (List the common basic words frequently used in this research field)	Supervised emotion learning · Real-time emotion detection · Twitter events analysis · Public emotion sensing · Text stream classification · Soft classification
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	for our project we will try to use the models to classify emotions in text messages and created a two-step framework, EmotexStream, to track emotions in real-time

Aspects	Paper # 5 (Title)
Title / Question (What is problem statement?)	Emotion Detection of Contextual Text using Deep learning
Objectives / Goal (What is looking for?)	<p>This research is looking for a way to detect and classify emotions from text based on context using deep learning. They want to understand the basics of emotion detection and look at the latest research in this area. They're looking for models that can understand text-based emotions and use them to build a word embedding and preprocess the data using things like normalisation and spelling correction. They use an LSTM model to predict emotions and get a higher F1 score than other models. In the future, they plan to expand this approach by using emoticon handling and emotion lexicons.</p>
Methodology / Theory (How to find the solution?)	<p>Word Embeddings: The researchers utilize word embeddings, particularly pre-trained embeddings, to construct a word representation model. This aids in capturing semantic meanings within the text.</p> <p>Data Preprocessing: To improve the input data quality, the paper applies data preprocessing techniques such as normalization and spelling correction. These steps help clean and standardize the text data.</p> <p>Emotion Prediction Model: The research employs a Bi-Long Short-term Memory (LSTM) model for predicting emotions. This model is well-suited for capturing context and sequences in text data, making it effective for emotion analysis.</p> <p>Recurrent Neural Networks (RNNs): The paper mentions the utilization of recurrent neural networks to track individual conversational states for emotion classification. This implies that the model considers the context and history of the conversation.</p> <p>Distributional Semantic Model: Additionally, the paper introduces a distributional semantic model for emotion classification in text. This model likely leverages word distributions to understand the context and relationships between words in the text</p>

Software Tools (What program/software is used for design, coding and simulation?)	python language and python library												
Simulation/Test Data (What parameters are determined?)	<table><tr><th>Type</th><th>Happy</th><th>Sad</th><th>Angry</th><th>Others</th><th>Total</th></tr><tr><td>Count</td><td>109</td><td>107</td><td>90</td><td>1920</td><td>2226</td></tr></table>	Type	Happy	Sad	Angry	Others	Total	Count	109	107	90	1920	2226
Type	Happy	Sad	Angry	Others	Total								
Count	109	107	90	1920	2226								
Result / Conclusion (What was the final result?)	This paper proposes a way to detect and classify emotions in a 3-way conversation using deep learning. The technique involves constructing a word embedding out of pre-trained word embeddings and using Bi-LSTM to predict emotions. The researchers' F1 score was 0.7189. This score is higher than other models, suggesting that their approach is effective.												
Obstacles/Challenges (List the methodological obstacles if authors mentioned in the article)	not mentioned												
Terminology (List the common basic words frequently used in this research field)	Contextual Conversation, Emotion Detection, Happy, LSTM, Machine Learning.												
Review Outcome (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	we will use huge amount of text data and will try to get a good score.and try to use Bi-LSTM Model.												