THE STUDY OF INCREMENTAL PROCEDURE WITH DEEP LSTM FOR MULTICLASS SENTIMENT ANALYSIS CONTEXT WITH ON EDUCATIONAL DATA

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ABSTRACT

In Sentiment Analysis, Machine Learning (ML) and Deep Learning (DL) algorithms used to understand people's nature and responses to events. Sentiment analysis widely used across various fields to study opinions or feedback and to improve services. It used to analyzed sentiment documents and classify their polarity as positive, negative, or neutral. Recent research work and studied that are ongoing are focused on Multiclass Sentiment Analysis (MCSA) aimed at analyzed textual documents and derived insights from them. A study used LSTM neural networks had presented a comprehensive analysis of Students academic performance measurement data that transformed measurement metrics into three sentiment categories. The educational systems involved in learning, decision-making, and evaluation process improved through the Students performance of Multiclass Sentiment Analysis. A study used Long Short-Term Memory (LSTM) neural networks for measured student's performance data achieved excellent performance with an accuracy of 99.89% through careful feature engineering, class balancing, and LSTM architecture optimization. The proposed research provided insights into the applications of these technologies across various fields of machine learning and deep learning including education, customer voice, workforce analysis, politics, digital marketing, and social media monitoring, and established a framework for this.

KEYWORDS

Opinion Mining, AI, ML, DL, ANN, NLP, LSTM, MCSA, Sentiment Analysis, Multiclass Sentiment

1. INTRODUCTION

In the internet world, everybody knows about Social Media, most of them actively participating in Social media activities [1]. In the social media activity like watching videos, giving Reviews in the form of comments, expressing opinion through likes or dislike, giving feedback in the form of rating on post. Given comments will be in the form of sentence, word or smile's.The use of social media has rapidly increased, and this has led to the creation of a large amount of content. There has been a heightened demand in society to study insight from people, making it essential to understand the role of sentiment analysis, where the insights of people's nature and their responses to any event analyzed.

Using the recent technology such as ML and DL through Sentiment Analysis and Multiclass Sentiment Analysis algorithms, has easy to find the opinion polarity of the given comments or feedback.

Educational assessment data contains rich information about student learning outcomes that can be analyzed to improve teaching strategies and educational policies. This research applies sentiment analysis techniques, traditionally used in natural language processing, to quantitative student performance data. By converting performance metrics into sentiment categories and employing advanced deep learning methods, created a novel approach for interpreting educational outcomes.

The Proposed study addresses three key research questions:

1. How can quantitative student performance data be functionally transformed into meaningful sentiment categories?
2. What is the optimal machine learning architecture for Multiclass Sentiment classification of performance data?

What insights can be gained from analyzing the relationship between performance metrics and derived sentiment categories?

In this article, types of sentiment analysis, process, working or implementation, application, research areas are explored.

2. MACHINE LEARNING

Artificial Intelligence (AI) offered various branches like Machine Learning. Machine learning implemented statistical methods and algorithms to enable machines to improve its experiences. Machine learning algorithms actively and effectively performing in the many fields including Natural Language Processing (NLP), speech recognition, Sentiment Analysis, computer vision, etc. The main task of machine learning is performing crucial role to decision making based on input data. The developed algorithms use historical data to find the patterns and relationship in provided data. These patterns uses as future references to predicting the solution of the unseen problem.

- *i)* *Model:* Real world problem hypothetically structured with mathematical representation using Machine Learning. Trained and built machine learning model using algorithms while training data.
- *ii)* *Feature:* It is a parameter of the selected dataset which can be measured during analysis. The Feature selections includes, Core metrics values.
- *iii)* *Feature Vector:* Feature vector is a set includes multiple in count and its purpose is to input value to training and predict the model.
- *iv)* *Training:* before making machine learning model, an algorithm provided trained data as input and found patterns in the that data and trained the model for desired results.
- *v)* *Prediction:* After making ready of the ML model, it predicted the output from the faded data.
- *vi)* *Target (Label):* Target or label is a predicted value got from the machine learning model.
- *vii)* *Under-fitting:* Model destroyed the accuracy of the ML model because of failed to decode the basic pattern in the provided data.
- *viii)* *Over-fitting:* ML model tends to learn from the inaccurate and noise data entries from the massive amount of data, and fails to characterize the data correctly.

A typical machine learning Process is going through the Training, Validation and Testing process.

Overall Machine Learning process working through 7 major steps:

i) *Collecting Data*: Machines initially learnt from the data that given them.
ii) *Preparing the Data:* The collected data are prepared for the processing. [1].
iii) *Choosing a Model:* Choose the appropriate models accordingly.
iv) *Training the Model:* Train the machine learning model along with the prepared dataset.
v) *Evaluating the Model:* Evaluate the trained model as per required feature.
vi) *Parameter Tuning:* Tuning the parameters in model.
vii) *Making Predictions:* make the appropriate predictions from the output gain from the model according to system.

a) Types of Machine Learning:

i) *Supervised Machine Learning:* The Algorithms generated information and learn from the labelled data from the dataset in Supervised Machine learning. E.g. images labelled with Tiger face or not. In this algorithm process object detection, segmentation and regression is happen.
ii) *Unsupervised Machine Learning:* The Unsupervised learning algorithms working on non-labelled data and learn from it. E.g. Making set of similar color sticks from bunch of sticks. In this algorithm process clustering and dimensionality reduction is happen.
iii) *Semi-Supervised Machine Learning:* These algorithm used both supervised machine learning and unsupervised machine learning data.
iv) *Reinforcement Machine Learning:* ML algorithms trained the software to for the making decisions to achieve the most optimal result. It is bit different from the supervised learning and unsupervised learning. In this algorithm perform to take note of the every positive result and make that the base of our algorithm. In the ChatGPT reinforcement techniques is used.

b) Classifiers:

i. *Naive Bayes* – Its simplicity and effectiveness encourages to implementation through it for sentiment Analysis and make it popular.
ii. *Support Vector Machines (SVMs)*–it has ability to handle high-dimensional and non-linear data.
iii. *Random forest* – It combined multiple decision trees for improvement in accuracy.
iv. *Gradient Boosting* –It combined multiple weak models for creation a strong predictor.
v. *Convolutional Neural Networks (CNNs)* – Effectively worked for text classification purpose, included sentiment analysis.
vi. *Recurrent Neural Networks (RNNs)* – It captured contextual relationships for sequential data.
vii. *Long Short-Term Memory (LSTM) Networks*– RNN type that exceled at handling long-range dependencies.
viii. *Logistic Regression* – A simple yet effective linear classifier for sentiment Analysis.
ix. *K-Nearest Neighbours (KNN*) –A basic classifier that can be effective for small datasets.
x. *Deep Learning-based Models (Transformers and BERT)* – These classifiers used to classify text like positive, negative, and neutral, or more fine-grained sentiment categories like very positive and somewhat negative.

Classifier was Chosen depends on the specific dataset, performance metrics, and computational resources [5].

C Overview of the machine learning Models:

Following six ML models are based on decision tree, NB, and random forest algorithms.These ML models are popular in sentiment analysis through withTf-Idf as wel as bag of words techniques [4] [20] study explored.

i. *Tf-Idf& Multinomial Naïve Bayes* – Data inserted into Multinomial NB Model and evaluates relevant word and creating matrix assigned to sequential Tf-Idf value refers for individually for word and tweet or comment.
ii. *Tf-Idf& Random Forest* – Implemented to converting words to numbers.
iii. *Tf-Idf& Decision Tree* – Produced matrix and inserted into a Decision tree Classifier.
iv. *BoW& Random Forest* – The combination of Random Forest algorithm and the BoW technique.
v. *BoW& Multinomial Naïve Bayes* – Data were inserted into the Multinomial Naive Bayes classifier along with converted of words into numbers with the BoW technique.
vi. *BoW& Decision Tree* –designed with the BoW technique by conjunction with the Decision Tree algorithm.

d. Features of Machine Learning:

i) The machine learning is not only learned by itself from its past data but also automatically improve it.
ii) The machine learning is working on data driven. Huge amount of data is generated in various institutions in everyday in various activity. Because of notable relationships in data, they can easily take decisions.
iii) In the reputed organization branding is very crucial and it is possible with to target oriented customer base.
iv) The machine learning is very similar to data mining technology because ML also concern and deals with various complicated data and large amount of data.
v) This Technology used to detect various patterns from the concern dataset.

e. Reasons for failure of Machine learning Projects:

There are many reasons to fail the machine learning projects to performing in industry or institutions. Some of them mentioned as follows:

Asking the wrong question while collecting data for making model, problem not understand and trying to solve the wrong problem, in the software requirement collection not having enough data collected, In software requirement data collection wrong data given means lack of right data, due to unnecessary data collection too much data stored, hiring the wrong people for data collection, lack of having the right yardstick, wrong tools chosen for data collection, and lack of having the right model for execution.

3. DEEP LEARNING

Deep learning is the one of the branch of ML. Deep learning strategy is like the multi-layer neural network means it worked as human brain. It learned from the huge data. Deep learning algorithms structured and performs like neural networks. By taking training deep learning network on huge amount of data, the developed algorithm learn to recognize the patterns and make the system adjusted on neurons. The developed and trained model is analyzed and respond its own for the new data. Natural Language processing (NLP) has achieved huge development due to Deep learning framework [2]. Deep learning models applied through NLP can grasp human language in surprising nuance, as it seemed like science fiction from last few years. Model can do multiple computations simultaneously due to optimization of GUUs in system. Without human intervention Deep learning model collected real-time data from multiple resources and analyzed it.

The Efficiency in linear algebra capabilities is the key element of deep learning framework. Tensorflow, PyTorch, mxNet, Keras, Caffe2, CNTK, mathlab, and PaddlePaddle frameworks are performed crucial role for Deep learning.

a. Deep Learning most commonly used 5 Models:

i. *Generative Adversarial Networks:*The Generative Adversarial Networks AI type, it creative with two sub-systems, those are fighting with each other to generated things or images on the basis of their ideology. First one called generator, which always tried to generate fake data. Example, images looks real one. Another one is called discriminator, which tried to spot what is fake. Above both sub-systems worked as the challenging task for each other, both got better in performance. The generator eventually learned to produce incredibly realistic results. In shortly it's like forger and art critic pushing each other to improve. The faker got better in mimicking task and the critic got better at spotting fake.
ii. *Auto Encoders:*The Auto Encoder is the smart system related to image understanding. This system shrieked some part of that image, and then tried to recreate the original one from created simplified version. The smart system is worked in three stages: one is compressed the input in smaller form like summary. Second is to Kept that compressed version. It's called bottleneck. Third is tried to rebuild original data from the bottleneck. Ex. Explaining the robber's facial scene by the facial witness in the process of making a sketch of robber.
iii. *Convolutional Neural Networks (CNN):* CNN [2] is a DL model specially used for spotting patterns in images [3]. Its Example is textures, shapes and edges. It used to find the object from the images and photos. This model is implemented to recognize photos in self driving cars.
iv. *Recurrent Neural Networks (RNN): A study* [3] explored that, the RNN model widely used for NLP functions, like sentiment analysis, machine translation as well as text generation. Recurrent neural networks categorized the meaning of words and sentences because they can learn to contextual word in a sentence.
v. *Long short-Term Memory Networks (LSTM): according to study* [2], LSTM networks is large-scale algorithm used for classification, Textual data processing, machine translation, time series analysis task, speech recognition, speech activity detection, robot control, healthcare, and video games.

a. Deep learning applications:

i. *Smarter Business Decisions:* AI-driven deep analytics tools don't just crunch numbers they uncovered sentiment and trends, measure customer emotions, and turn complex data into easy to understand visuals.
ii. *Personalized Recommendations:* AI Deep learning based made Netflix, Spotify's, and YouTube studied people's habits to recommend exactly what they'll love.

iii. *Machines that "See" Like Humans:* Deep learning taught computers to understand images in ways that once thought impossible. Its example is, from unlocking the patient’s phone with a glance to helping doctor’s spot diseases in scans.
iv. *Voice Technology that Understands You:* Recent AI Technology can listen to spoken words and turn them into text faster and more accurately than a person typing by hand.
v. *AI for a Greener Future:*Google isn’t just making AI smarter it’s making it greener by using deep learning to optimize its data centers.
vi. *Organizing the Chaos of Language:* AI does read text; it sorts, labels, and makes sense of it helping search engines and businesses manage information at scale.
vii. *Detecting Emotions in Words:* Through sentiment analysis AI sensed frustration, excitement, or satisfaction in customer reviews giving companies real-time insight into how people feel.
viii. *The Eyes of Self-Driving Cars & More:* Deep learning helped AI to recognize objects, faces, and even road signs for powering innovations from social media filters to autonomous vehicles.

b. Deep learning Disadvantages:

While deep learning drives cutting-edge AI advancements, it’s not without its hurdles:

i. *High computational cost:*Training deep learning models demanded heavy-duty hardware, like powerful GPUs and vast memory making it expensive and time-consuming.
ii. *Over-fitting:*Models became "too good" at learning training data, failing to generalize to real-world scenarios. This often stems from insufficient data, overly complex architectures, or weak regularization.
iii. *Lack of interpretability:*With their intricate layers, many DL models acted as inscrutable "black boxes," made it hard and interpreted predictions or debug biases.
iv. *Data Dependency:*Garbage in, garbage out i.e. Noisy, biased, or incomplete data directly undermined model performance.
v. *Data prvivacy and security concerns*: Massive datasets raised concerns, malicious use could enable identity theft, financial fraud, or breaches of privacy.
vi. *Lack of domain expertise:*without deep subject-matter knowledge, it was easy to misapply algorithms or mis-define problems.
vii. *Unforeseen consequences*: Biases in training data leaded to discriminatory outcomes, sparking ethical dilemmas.
viii. *Black box models*: These models only known what they’ve been taught; unfamiliar scenarios often stump them.

4. TRANSFORMER

Transformer technique is used to creating general model regulated for a certain task. Transformers has cause to change sentiment analysis with influential manner to process and understand natural language. In Sentiment Analysis to classified a piece of text based on the emotional tone, and conveys its polarity as positive, negative, or neutral polarity.

A study related to Transformers introduced that, it is excel in handling sequences of data like sentences or documents. It can also captured complex lexical relations, even those that may be far apart in a sentence [16].

a. Mechanisms for context with sentiment analysis:

Transformer model is mostly used in industrial applications and research activity. Transformer model implemented with following mechanisms context with sentiment analysis:

i. *Transformer Architecture and self-Attention:* The transformer is used in various applications to get insight on the data. Here, Because of the self-attention mechanism, it possible to enables to developed model to making predictions, not only just focusing on a single part of the sentence, it consider the entire context of a sentence. This mechanism acts as key components of this model.
The self-attention mechanism worked as multipurpose actions. By assigning the work, different attention scores to each word in a sentence relative to others. In this helping the model to decide which section of the provided text are most relevant for understanding the sentiment insight it. This mechanism also allowed transformers to understand nuances and dependencies within the text. The example of it, in the phrase or sentence "The place was not bad," a transformer model would correctly understand that "not bad" could convey a positive sentiment.

ii. *Pre-trained Transformer Models:* The transformer model increased scope in various industry, institutes and research for development of the applications; some pre-trained transformer models introduced by researcher for that purposes.Out of these Pre-trained transformer models like, RoBERTa and GPT were widely used for sentiment analysis activity.

The traditional models used to processed text in single direction only like left-right either right-left. This whole process BERT model acted overall sentence at once. This is what helping to understand the meaning of words in both directions. BERT was a significant step forward in natural language understanding because it used a bidirectional approach to context. This ability to understand context more holistically improved its performance in sentiment classification tasks explored in study [17].

GPT made on the transformer based. It is working as autoregressive, generating text word by word in a left-to-right manner. GPT shown good performance in text generation. It has also optimized well for sentiment analysis tasks, concern with large amounts of labelled data to classify sentiment strategically [18]. The RoBERTa (Robustly optimized BERT approach) technique is a variation of BERT technique. It has been revealed to excel BERT in much activity, containing sentiment analysis. Researcher trained it with larger data sets and refined for performance via removing some of BERT's training parameters [19].

b. Advantages of Transformers context with Sentiment Analysis:

The main advantages of transformers in sentiment analysis includes:

Contextual Understanding: Transformers can recognized the perspective of a sentence, not just alone words but for which is crucial for sentiment analysis. For example, they can differentiate between "I like this!" (Positive context) and "I like this, but it is too costly!" by recognizing adjacent context of it.

Transfer Learning: Through the optimizing pre-trained transformer models, sentiment analysis tasks get benefited from the huge amounts of data the models were initially trained on, for enhancing precision accuracy with versatile training data.

Long Sequences Handling: The RNNs struggled with long-range dependencies in series. The Transformers, on the other hand handled long-range relationships streamlined because of to their attention mechanism.

c. Data-driven insights of transformer:

The Recent studies and benchmarks have revealed that transformers outperform compared with other methods like LSTMs or CNNs in sentiment analysis. A researcher explored that, BERT has been demonstrated to achieve innovative outputs in sentiment classification piece of work on datasets like IMDb and SST-2 (Stanford Sentiment Treebank) [17]. In the same way, RoBERTa has also outperformed previous transformer models on various sentiment analysis criteria, demonstrating its strength and efficiency [19].

d. Challenges and strategy of Transformer:

While transformer-based models have significantly advanced sentiment analysis, each has its own obstacles:
Computational Cost: Transformers are computationally costly because of requiring significant resources for training and refining.

Interpretability: Transformers performed well, but their unseen mechanism made them challenging to interpret. It could be generate problem to comprehension of domains because, it's very necessary to understand a model's decision reason.

Regardless of these challenges, transformer-based models are probably to remain at the forefront of sentiment analysis, as research activities continue to explore at improving generalization, efficiency and interpretability.

5. ARTIFICIAL NEURAL NETWORKS (ANN'S)

Artificial Neural Networks (ANN's) are designed and structured computational model based on human neural networks system and it also functions like that. In terms of computer science, it acted likes An Artificial human nervous system. It could receive, processed and transmitted information. Various layers like, Input layer, hidden layer and output layer consisted for performing specific tasks in Artificial Neural Network.

A neural network method instructed computers system to process data as human brain manipulation data. Deep learning based RNN structure created adaptive system used complex neurons layered structured which lean from their mistake and solve the complications like summarizing documents and pure face recognition.

a. Working of Neural Networks:

As we discussed above, the human brain is the inspiration behind the creation of neural networks. Complex structured human brain cells or neurons were highly interconnected network. It helps human to send electrical signals to each other. Similarly, to solve a computational problem ANNs an algorithm made up of Artificial Neurons.

b. Training the network:

The Deep Neural Networks (DNNs) made up of Artificial Neural Networks. The network model trained with the number of epochs or iterations, which had initialized and then observed the change in loss through time. In the process of training the model, the current loss decreased with the increase in the epochs as observed and predicted that proposed model increased accuracy.

c. Applications of Artificial Neural Networks in terms of Deep learning:

The DL technology is widely used in the various fields for different-different purposes. Some of trending applications are mentioned as below:

- *i.* *Pattern Recognition:* In huge amount data have the similarity and regularity in the data. Pattern recognition is the process of data analysis that used algorithms to automatically recognized pattern and regularities in the data.
- *ii.* *Speech Recognition:* Speech recognition process spoken words identified and converted them into readable text. Speech recognition widely used in research of computer science, computer engineering. NLP had ability to process human created text, insights it and meaning from text and documents.
- *iii.* *Audio Recognition:* In the audio Recognition Process algorithms had ability to received and interpreted dictation or to understand and perform spoken command. The technology used in Artificial Intelligence (AI) of Apple, Amazon, Google as Intelligent Assistants like ‘Siri’, ‘Alexa’ and ChatGPT sequentially.
- *iv.* *Video Recognition:* In the process of Video Recognition detected patterns used to identify objects at different angles and distance or to find hazardous events from video using face detection or movement analysis.
- *v.* *Text Recognition*: The text recognition process involved evaluating the text and translating the characters into code uses for data processing. OCR (Optical character recognition) used for text processing. Google’s LENS is also the best example to it.
- *vi.* *Recommendation engines:* The Artificial Neural networks can tracked user activity from history to develop personalized recommendations. The application of recommendation engines implemented by ‘Amazon’, ‘Mesho’, and ‘flipchart’ to suggest the matching products to the customer on the basis of customers buying and browsing history.

6. SENTIMENT ANALYSIS

A Study [13] explored that, NLP used Sentiment Analysis or opinion mining technique to determined emotional tone express in a piece of text or sentence. Sentiment analysis interpreted and classified the emotions like positive, negative or neutral within text, video or audio data used by DL and ML algorithms.

Sentiment Analysis involved, identification and classification of subjective information from textualdata, like customer reviews, survey responses, and social media posts. It identified that the expressed sentiment had positive, negative or neutral. Sentiment analysis modelled a classification problem, subjectivity problem and polarity problem to resolve it.

a. Sentiment Analysis Scope:

i) Sentence level [2]

A piece of text or sentence those expressed opinions like positive, negative or neutral called as polarity of classification.

ii) Document level

To advancement of sentence level analysis to insight of documents.

b. Process of Sentiment Analysis:

Sentiment analysis technique used in DL and ML algorithms through Natural Language processing, to automatically identification of the emotions behind conversations and feedback. Sentiment analysis process involved following activities:

Data Collection: The collected textual data i.e. dataset.
Data Processing: Clean and prepared the text for classification.
Data Analysis: Analysed the taken datasets.
Data Visualization: Visualized and shared the insights of the text.
Feature Extraction: Extracted vital information from the text data.

c. Applications and research scope of sentiment Analysis:

Cutting-edge era, numerous growing fields' required new applications to get survive from the advanced technologies. The demands are increased in huge amount from the resources of the various fields, use of sentiment analysis also growing fastest. To making the desire model as requires of the industry sentiment analysis doing its crucial roles. Some of these desirable fields such that: Politics, Social media monitoring, Voice of Customer (VoC), Brand monitoring, Marketing, Education, Healthcare, Workforce analytics and voice of employee, and Human resource and more.

i. *Politics:* Sentiment analysis involved in text analysis to identify and extract the subjectivity of information from social media generated text data [6]. In the context of election related data prediction, sentiment analysis used to guess public opinion to predict the likely winner or loser of an election.
ii. *Voice of Customer (VoC):* Sentiment analysis in term of Voice of the customer (VoC) process collected, analyzed, and interpreted customer feedback to understand their needs, wants, and expectations. Sentiment analysis of Voice of the customer understood that how customers felled about the product or service. The purpose behind sentiment mining for Voice of the customer that, to improve customer satisfaction and inform to further business decisions [7], understand customer reviews for products/services, analyzed customer support interactions, identify pain points and areas for customer improvement and categorized survey responses to gauge customer satisfaction levels with more granularity.
iii. *Brand monitoring:* The brand Monitoring identified the possible damage from negative signals regarding brand's overall standing, stature and esteem. A study [8] explored, the marketing-strategy depended on digital marketing strategies, person-brand strategies brand architecture strategies, as well as corporate socio-political activism. A successful brand stewardship required to monitor and tracks these marketing-strategy-related sources of reputational risks to relate to the products brand to achieve these strategy.

iv. *Workforce analytics and voice of employee:* In the recruitment process the term Workforce analytics and voice of the employee (VoE) are both valuable tools for HR persons, but they varied in their focus and certain use. The Workforce is a process that involved collecting and analysing employee data to improve workflow to make data-driven decisions. It supported to HR heads to identify trends, pinpoint high-potential employees, and improve recruitment, retention, and hiring processes [9].

Voice of the employee tool gave opportunity to the employees to express their opinions, concerns, and ideas to heads and decision makers. According to Research, statistical results demonstration workforce analytics negatively affected on fulfilment at work.

A study [10] explored that, the work volition reduced the negative relationship in between workforce analytics and fulfilment at work. It also explored significant of work force and negative relationship between fulfilment at work and work volition.

v. *Marketing:* Research [11] indicated the trend of digital marketing on purchase intentions continuously increased and it gave a better understanding of the role of digital marketing to influenced purchase intentions. In other study [12] explored that, to foster consumer trust in sustainable marketing strategies the significance of transparency and effective communication is necessary. To gauging consumer preferences and identifying unmet needs to analysed competitor performance and public perception and predicting market trends.

A research study [3] explored that DL algorithms, like as LSTM, had the potential to extract knowledge from huge volumes of data with pure accuracy and reliability than manual approaches of sentiment analysis. A Study implicated improve their products and services to the businesses seeking by leverage customer feedback.

In a case study [14] of banking, uncovered general sentiments toward banking field as well as insight that sentiments shifted to opinion while marketing activities and global events. Study explored that, Sentiment analysis performed data driven and real-time assessment to developing business strategies and improving customer relationships in industries.

Vi. *Social media monitoring:* The cutting-edge digital era social media platform are fastest grown. The forums needs to disclose to each other on the various topics. It is very crucial to understand and capitalize on remark made as various fields including social media and other [15] like, Tracked brand perception and public opinion on specific topics, campaigns, or events, Identify trending sentiments and potential crises early and analysed political discourse and public reactions to policies or candidates.

vii. *Healthcare:* Analysed patient feedback to improve services and patient experience and monitored public health discussions and sentiments around specific health issues or treatments.

viii. *Human Resources:* Analysed employee feedback and survey responses to assess morale and identify areas for organizational improvement.

ix. *Education:* In the education system Sentiment analysis used for the student feedback mining to enhance teaching and learning process. Sentiment analysis do better assistance in educational institutions for evaluating their teaching and learning process by mining the sentiment from student’s opinion. With use of an advanced sentiment analysis technique, it is possible to find sentiment orientation of student comments without human being enrolment. Researcher’s study explored that Sentiment analysis performed vital Role in the enhancement of educational system like pedagogical concepts, decision making and evaluation process [5]. A study demonstrate that, applied method for sentiment analysis to higher education research and complex relationship between communication and education [15].

7. MULTICLASS SENTIMENT ANALYSIS (MCSA)

Multiclass Sentiment Analysis (MCSA) is an extension of traditional sentiment analysis, where instead of classifying text like "positive" or "negative" (i.e. binary classification), it categorized text into more than two sentiment categories. Multiclass Sentiment Analysis used Deep Learning algorithms, Machine learning algorithms through NLP to determine the emotional tone expressed in a piece of text or sentence. While binary sentiment analysis might categorized "The Book was great!" as "positive" and "The service was bad" as "negative," Multiclass Sentiment Analysis (MCSA) gone further. It could classify "The Book was great!" as "very positive," "positive," or "enthusiastic," and "The service was just okay" as "neutral" or "mildly negative," rather than just a blanket "negative." Common multiclass categories often included: Positive, neutral, negative, Extend to more granular emotions, Negative, Very Negative or Strongly Negative, Angry, Sad, Happy, Surprised, Fearful, Curious, Disgusted, Litigious, and Uncertainty. The Multiclass Sentiment Analysis also offered the multi-tier architecture for the multiclass classification of sentiments of the text. In the above multi-tier architecture used Naïve Bayes, SVM and Decision Tree for trained the classifiers [13].

Multiclass Sentiment Analysis Techniques: various Techniques has to Multiclass Sentiment Analysis. Some of them are explore as following:

Rule-Based Approaches: These approaches rely on lexicons and a set of hand-crafted rules to determined Multiclass sentiment. While simpler, they struggled with context, sarcasm, and evolving language. VADER (Valence Aware Dictionary and sEntiment Reasoner) most popular tool optimized for text collected from social media and other platform worked lexicon-based Sentiment Analysis.

Machine Learning Approaches: It is data-driven approach. They learned patterns from labelled data to make predictions. Array of algorithms used, as traditional ML to DL in this approach.
Hybrid Approaches: In this approach, combining rule-based methods with machine learning sometimes leveraged the strengths of both rule based approach and machine Learning approach, for Ex., using a lexicon to augment features for a machine learning model.

Aspect-Based Sentiment Analysis (ABSA) Approaches: A study [5] explored that, this gone a step further by identifying the specific aspects and features of product or service that a sentiment refers to. For example, in "The writing speed is excellent, but the poor sentence building," ABSA would identify "writing speed" as positive and "Sentence building" as negative.

Python Libraries for Multiclass Sentiment Analysis:

While implementing algorithms to perform multiclass sentiment analysis Python has a rich ecosystem of libraries for implementing multiclass sentiment analysis:

NLTK (Natural Language Toolkit): libraries used throughNLP in Python. It provided everything from tokenization and stemming to basic classifiers and sentiment lexicons. While it's a solid starting point, it often worked best when combined with other tools for more advanced, multiclass sentiment analysis.

TextBlob: TextBlob offered most user-friendly interface and it built on top of NLTK. It performed basic sentiment analysis by giving polarity (how positive or negative something is) and subjectivity scores. Out of the box, it's generally used for binary sentiment (positive/negative), but customized it to classify multiple sentiment categories if needed.

*VADER (Valence Aware Dictionary and sEntiment Reasoner):*A popular Tool used for sentiment analysis included with NLTK, designed especially toanalyzing social media text. It broke down sentiment into positive, neutral, and negative components, along with a compound score. It used these scores to build own sentiment categories. Example, labelling text as "very positive," "neutral," or "slightly negative" on the basis of thresholds.

scikit-learn: Traditional ML used in Python Scikit-learn library. It included popular classification algorithms like Naive Bayes, Logistic Regression, SVMs, and more. It also helped with text feature extraction included TF-IDF or Bag-of-Words while model training, and evaluation. It's often used alongside NLTK or SpaCy for text pre-processing.

*SpaCy:*SpaCy is known for being fast and production-ready. It offered advanced features like named entity recognition and syntactic parsing. While it didn't included built-in sentiment analysis tools like NLTK, it's a powerful foundation for building custom pipelines and integrating machine learning models for multiclass classification.

Transformers (Hugging Face): To state-of-the-art performance the Hugging Face's Transformers library is reliable. It included pre-trained models like BERT, RoBERTa, and GPT that excel at text classification tasks. These pertained model used to developed own models on own dataset to build high-performing multiclass sentiment classifiers. These models often outperformed traditional methods, especially when worked with large and diverse text datasets.

PyTorch / TensorFlow / Keras: These are deep learning frameworks that allowed to build custom models from the ground up. Whether used CNNs, LSTMs, or even building own transformer-based models, these libraries gave full control. While they required more effort and expertise, they're ideal for building highly customized or research-level sentiment analysis systems.

8. RESEARCH METHODOLOGY

8.1. Overview of Implementation Through LSTM Deep Learning Models:

Fundamentally in deep learning based models will be implemented in terms of (LSTM) neural networks at the time of execution with the Tensorflow and Keras libraries [4]:

i) *Simple LSTM* – The Keras embedded first layer of classifier mostly used in text data. This layer accepted only integer values. The result of previous layer considered to the next layer of SpacialDropout1D. The process performed to overcome on the over-fitting problem, and after that, the data recognized as 3 LSTM with 3 batch normalization layer by shape 3, decided type of sentiment carry in the assessed tweet [4].

ii) *GloVe LSTM* – Pre-trained embedding utilized with 3 LSTM with 3 Dropout layers.

iii) *BiLSTM* –The content of the text summarized with forwards and backwards way and combined with a SpacialDropout1D.

iv) *Gensim LSTM* – The pre-trained word embedding consisted acquired from the data at disposed.

v) *Bert LSTM* – The generated output inserted through layer in a BiLSTM, along with Dropout layer. The output inserted in *sequence output.* To the rest of the model for purpose oriented work therefore, it needed to contain the word embedding.

vi) *Bert Tokenizer LSTM* –The token did word splatted into tokens to evaluate its behaviour throughout the data and receives input based on word Piece Tokenizer.

vii) *Text & Numerical Data LSTM* – received input as a numerical data. After normalization of this data, constitute the input of a dense layer.

8.2. Implementation Process of Methodology

Accordingly mentioned deep learning technology did the sentiment analysis of in various application. The deep learning LSTM classifiers which seen above used to implemented sentiment analysis techniques on textual data in various forms like numeric or textual. Followed by implementation on data got positive, negative and neutral forms of the result data. The result used to evaluation various decision making purposes [4]. The Use of deep LSTM method implementation on the textual data happen through in three important phases mentioned as follows.

i. *Text Pre-processing phase:*

The collected textual data pre-processed and made it ready to easy implementation with deep LSTM method in the text pre-processing phase [4]. It had many steps to process on textual data.

a.Conversion of Characters to lowercase and the hyperlinks are removal: In the linguistic view hyperlinks did not made addition in information. To made similarity in format of all textual data conversion of lowercase was necessary. In this activity of data pre-processing capital letters converted into lower case letter and hyperlinks removed.

b.Elimination of mentions and hashtags: On the Social media conversation to gaining the attention of certain person used mention and hashtags feature of social media. Apart from this it didn't had any other intention behind its use. Here, in this activity mentions and hashtags removed. According to many research study [8] [12], Deep learning techniques respond to as much information. The meaning of the sentence did not change during the implementation with textual data. Therefor stop word removal phase not implemented here.

c.Contractions Correction (transformation word into initial form): On the social media platform communication, everybody using the shortened form of word to increase the communication speed and made easy communication. Here many lots of words get converted into the shortened versions. It means they got shortened forms from their initial form. The shortened words transformed into their initial forms to decrease the cost of calculation and dimensionality for concise and complete version of the words.

d. Part of Speech (POS) tagging: Each token acquired a special POS tag and a POS tagging. POS tag used to indicate and contain additional information about grammatical category i.e. noun, pronoun, adjective etc.

e.Utilization of 'autocorrect': The 'autocorrect' library used to replaces the words that considered not to be correctly spelled but important accordingly to it.
*f.Tokenization :*In this activity a 'text' is disintegrated into smaller sections was called 'tokens'. In the implementation process each terms of every comment or phrase stored in token list, by natural order its text's tokens appeared.

g.Lemmatization: In lemmatization process inflected words reduced and converted into a root word those words existed in the vocabulary performance. Previously produced POS tags utilized by WordNetLemmatizer and each word form comment or phrase passed for their base or dictionary form.

ii. *LSTM Model Architecture Phase:*

The Proposed LSTM model consists of following sequential Architecture of Python Code:

```
model = Sequential ([
   LSTM (64, input_shape = (1, input_shape),
   Dropout (0.2),
   LSTM (32),
   Dropout (0.2),
   Dense (32, activation='relu'),
   Dense (n_classes, activation='softmax')
])
```

The LSTM architecture [4] based on related to the RNNs category. It eliminated the exploding the gradient problem effective long term dependencies in modelling. The used mechanism in this process has ability to perform an action like, which information is important to remember, update and to pay attention.

In the proposed model Key architectural decisions included, Two LSTM layers (64 and 32 units) for hierarchical feature learning, Dropout layers (p=0.2) for regularization, ReLU activation in the dense layer for non-linearity, Softmax output for multiclass classification, Adam optimizer along with learning rate 0.001, as well as Categorical cross-entropy loss function.

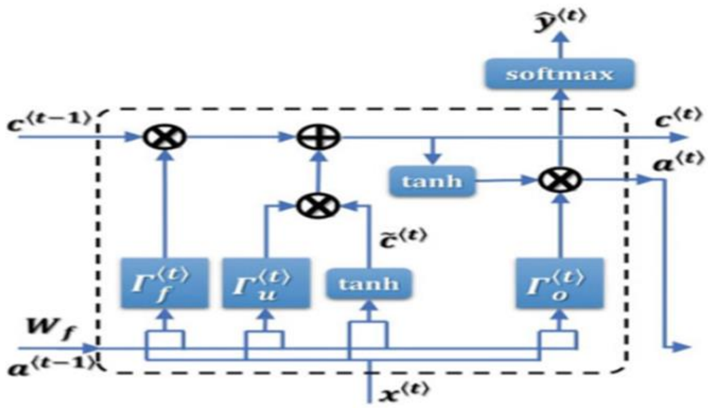

Fig. 1. LSTM architecture

According to above figure (fig. 1) and a research study [4] explored that, the following mentioned equations indicated the procedural sequence of LSTM operations.

$$\Gamma_u^{\langle t\rangle} = \delta\,(W_u\,[a^{\langle t-1\rangle}, x^{\langle t\rangle}] + b_u) \qquad (1)$$

In the first equation accordingly above mentioned fig. sigmoid function in update gate used to decide that which [2] explored information updated and ignored by merging $\chi^{(t)}$ and $\alpha^{(t-1)}$ in the memory cell $c^{(t)}$.

$$\Gamma_f^{<t>} = \delta\,(W_f\,[a^{\langle t-1\rangle}, x^{\langle t\rangle}] + b_f) \qquad (2)$$

In the Second equation forget gate consisted of sigmoid function. The sigmoid function used to take the current input according to [2] of cell i.e. $\chi^{(t)}$ and the output of last one i.e. $\alpha^{(t-1)}$, to take decisions that which one parts of the old output removed in order to free a substantial parts of the memory.

$$\Gamma_0^{<t>} = \delta\,(W_0\,[a^{\langle t-1\rangle}, x^{\langle t\rangle}] + b_0) \qquad (3)$$

In the Third Equation output gate consisted with sigmoid function. It used to decided which memory cell information extracted.

$$\tilde{c}^{\langle t\rangle} = \tanh (W_c[a^{\langle t-1\rangle}, x^{\langle t\rangle}] + b_c) \quad (4)$$

In the Fourth Equation, $\tilde{c}$ layer have the hyper function tanh. It used to create a vector value for all possible values from the new inputs.

$$c^{\langle t\rangle} = c^{\langle t-1\rangle} \times \Gamma_f^{\langle t\rangle} + \tilde{c}^{\langle t\rangle} \times \Gamma_u^{\langle t\rangle} \quad (5)$$

In the Fifth Equation, multiplied output accordingly [2] of the equation 2 and 4 for updated the new memory cell. To getting $c\langle t\rangle$, the old memory i.e. $c\langle t-1\rangle$multiplied with the forget gate.

$$a^{\langle t\rangle} = \Gamma_0^{\langle t\rangle} \times \tanh c^{\langle t\rangle} \quad (6)$$

The Sixth Equation shown that, the memory cell status. By the composing of *tanh* function, it created a vector of all possible values and multiplied with the output gate. Got the hidden state by this process and it forwarded to the next unit of the LSTM.

iii. *Word embedding Phase:*

Word embedding technique [4] used to sequencing the collected text and representing words in a number form. This technique performed a key part in NLP and ML. According to study [2], the word embedding technique input layer consisted for the matrix representation of documents and sentences, without of the images pixels. Study also explored that every row of the matrix is a vector representation for the word and character. Study [2] concluded, these types of vectors are called word embedding or character embedding. During manipulation of these technique, similar word with similar meaning represented by similar vectors. The distance and direction between vectors indicated the similarity and relationships between words. The words that had closer together in the vector space were more likely to had similar meanings.

The most common word embedding layers are as follows:

Embedding Layer: the representation of word performed with help of various neural network models.

Word2Vec: developed pre-trained word vector represented.
GloVe: an extension of the Word2Vec technique.
Bert: Bert technique performed based on transformers.

In study, utilized of above mentioned techniques implemented by LSTM- DL models for Multiclass Sentiment Analysis (MCSA) in education field and applicable for other field discussed above.

8.3. Evaluation

a) ***Dataset Description***

According to many studies, Sentiment Analysis datasets mostly included: Tweets, posts, debates, messages, comments, blogs, hash-tags, consumer reviews on Google Play, review about restaurants, multi-domain review about books, electronics and kitchen appliances, reviews about online products, hotels and locations (places), star ratings about products, emoticons, and images. A dataset defined as, a collection of related, discrete items of related data that may be accessed individually or in combination or managed as a whole entity. To testing the performance of sentiment analysis algorithm, dataset play the vital role in that. In present study student assessment performance dataset identified and selected the datasets for multiclass sentiment analysis. The source of dataset *labelled text* or tweets or comments through the social media on educational scenario. After applying the deep learning models on dataset got the accuracy achieved on that [2]. To get desired result chosen the data in a certain period.

Table 1: The Multiclass Sentiment Classification

Sr. No	Classification	Abbreviation	Description
1	True Positive	TP	SamplesCorrectly classified in terms of sentiment
2	False Positive	FP	Considered samples by classifier to belong to a class when they actually do not
3	False Negative	FN	Classified in a class other than the one they truly belong to
4	True Negative	TN	All other elements

The collected dataset classified into *positive, extremely positive, neutral, negative, extremely negative* sentiment [4]. The classification of data performed to categorize the *labelled text* or tweets or comments in mentioned categories to calculate the number of *labelled text* or tweets or comments. A study [2] explored, categorized data organized into various type of data structure. While test the performer of Multiclass Sentiment Analysis (MCSA) dataset played a vital role.

In the proposed study, used the *Student_Assessment_Performance* Dataset (Noey, Professor at Holy Angel University, Central Luzon, Philippines, 2025), consisting of 1943310 initial and 334,333 after pre-processing labelled text samples across 20 emotion categories, available of Kaggle website.

Data source: Kaggle (Delaware Smarter Balanced Assessments).

b) ***Dataset Pre-processing***

After the Chosen and trained a ML model on the labelled data. The evaluation phase for tested the performance of the designed model. Proposed Model evaluated based on their ability to classify *labelled text* or tweets or comments sentiment effectiveness. In this phase of evaluation performance of model measured by metrics of evaluation of a system prediction, such that accuracy, recall, F1_score and precision etc. [4]. As the nature of Multiclass Sentiment Analysis value has multiple counts presented in evaluation like accuracy, precision, F1_score and recall. Execution of mentioned values applied by the one vs. all approach.

As discussed above Pre-Processed the initial task in the data set evaluation. The Data pre-processing pipeline included:

i. Sentiment Label Creation: The sentiment label created as, Negative: 0-50% proficiency, Neutral: 50-75% proficiency, and Positive: 75-100% proficiency.
The sentiment label created using following python code:

```
df ['sentiment'] = pd.cut ( df ['PctProficient'],
bins = [0, 50, 75, 100],
labels = ['Negative', 'Neutral', 'Positive'],
include_lowest=True)
```

Table 2: Data Description.

	School Year	Tested	Proficient	PctProficient	ScaleScoreAvg
Count	943310e+06	532814	359837.000000	359837.000000	344333.000000
Mean	021840e+03	127.36057	59.552934	37.774986	1651.329312
Std	401563e+00	736.461592	358.011887	19.153676	1003.280559
Min	015000e+03	15	5.000000	0.630000	6.730000
25%	021000e+03	24	9.000000	22.830000	573.250000
50%	022000e+03	41	18.000000	35.290000	2420.050000
75%	024000e+03	89	41.000000	51.060000	2490.230000
Max	024000e+03	67124	34596.000000	100.000000	2799.960000

Table 3: Classification Report

Parameter/ Sentiment	Precision	Recall	f1-score	support
Negative	1.00	1.00	1.00	51475
Neutral	1.00	1.00	1.00	51475
Positive	1.00	1.00	1.00	51475
Accuracy	1.00	1.00	1.00	154425
macro avg	1.00	1.00	1.00	154425
weighted avg	1.00	1.00	1.00	154425

The confusion matrix demonstrates perfect classification across all sentiment categories, with no misclassifications evident in the normalized matrix.

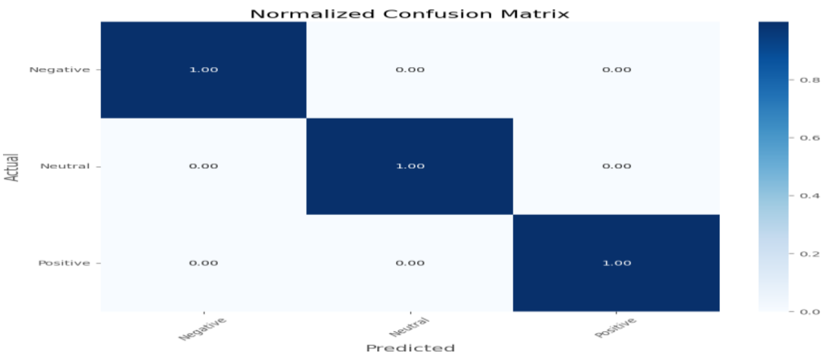

Fig.2: Normalized Confusion Matrix Report for Actual & Predicted value

c) *Feature Analysis*

Feature Selection: According to the *Student_Assessment_Performance*Data set mentioned above Feature selections included Core metrics: PctProficient, ScaleScoreAvg, Tested, Proficient and Categorical encoding of Grade levels (3rd-11th grade).

Table 4: Feature Description Report.

	Proficient	PctProficient	ScaleScoreAvg
count	359837	359837	344333
mean	59.552934	37.774986	1651.329312
Std	358.011887	19.153676	1003.280559
Min	5	0.63	6.73
25%	9	22.83	573.25
50%	18	35.29	2420.05
75%	41	51.06	2490.23
Max	34596	100	2799.96

The feature correlation matrix revealed as following mentioned Parmeters:

i) Strong positive correlation (0.82) between PctProficient and Proficient
ii) Moderate correlation (0.65) between ScaleScoreAvg and PctProficient
iii) Expected relationships between grade levels and performance metrics

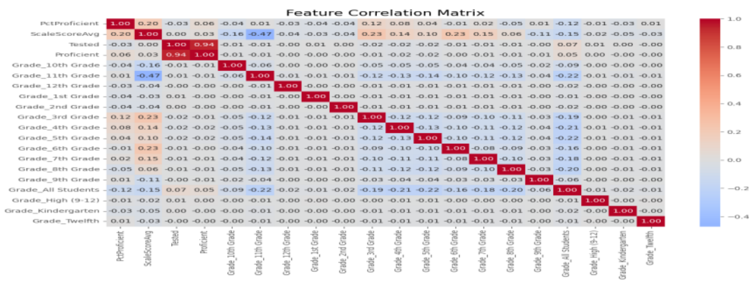

Fig. 3: Feature Correlation Matrix Report

d) *Training Configuration*

Training Dynamics: The training process showed that the Rapid convergence within first 5 epochs, Stable validation performance throughout training and Minimal over-fitting due to effective dropout regularization. While training phase, confirmed the Deep LSTM proposed model with specific parameters to optimize its performance.

In the Proposed model includes following training configurations: The *Student_Assessment_Performance* dataset trained on the proposed model and have done 30 training epochs, Batch size of 128, and 80-20 train-test split with stratified sampling. Batch size denoted in evaluation process the number of samples processed in each training iteration of proposed model and value was chosen based on computational constraints and size of dataset. The value was determined through the experimentation to balance training time and convergence of present Deep LSTM model. The model also given Feature scaling using Standard Scalar and One-hot encoding for Multiclass labels.

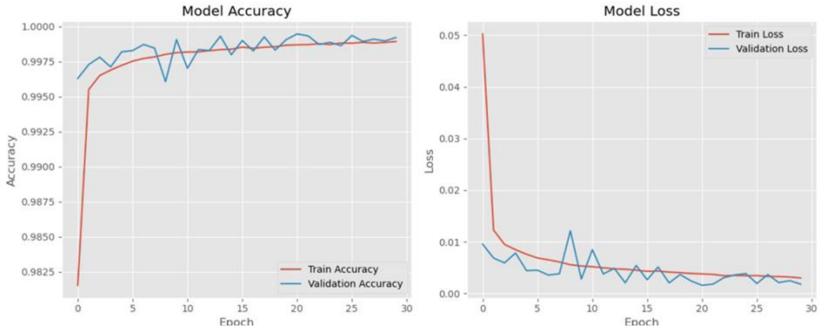

Fig. 4: Model accuracy & Model Loss Report

e) *Model Performance*

The performance of the evaluation of indices in terms of Multiclass Sentiment Analysis (MCSA) used the following mentioned formulae. The values of the evaluation indices determined with the helped of following formulae:

$$\text{Accuracy} = \frac{TP+TN \qquad TP+TN}{TP+FP+FN+TNTP+FP+FN+TN} \tag{7}$$

$$\text{Recall} = \frac{TP+TN \qquad TP+TN}{TP+FP+FN+TNTP+FP+FN+TN} \tag{8}$$

$$\text{F1\_score} = \frac{TP+TN \qquad TP+TN}{TP+FP+FN+TNTP+FP+FN+TN} \tag{9}$$

$$\text{Precision} = \frac{TP+TN \qquad TP+TN}{TP+FP+FN+TNTP+FP+FN+TN} \tag{10}$$

The Proposed Deep LSTM model achieved exceptional performance metrics for the Multiclass Sentiment Analysis (MCSA) for the *Student_Assessment_Performance* data set. The model achieved the performance as followings:

i. Training Accuracy: 99.89%.
ii. Validation Accuracy: 99.92%.
iii. Precision, Recall, F1-score: 1.00 for all classes.

f) *Sentiment Distribution and Handling with Imbalance Classes*

The initial Sentiment distribution showed significant class imbalanced: Negative: 257,374 (74.7%), Neutral: 74,966 (21.8%) and Positive: 11,993 (3.5%) after SMOTE (Synthetic Minority Over-sampling Technique) applied to balancing to each class of 257,374 samples.

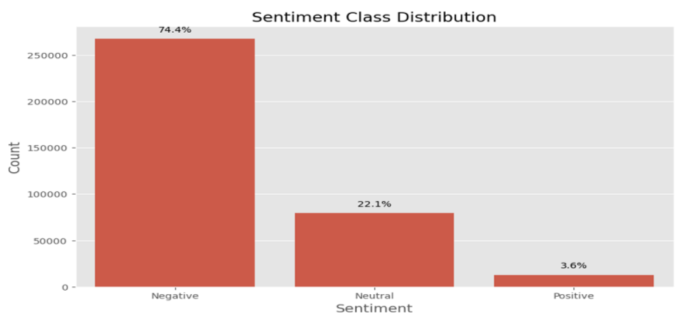

Fig. 5: Sentiment Class Distribution

g) Result Discussion

i. *Key Findings*

1. **Performance Interpretation**: According to model analysis with the *Student_Assessment_Performance*data set, high accuracy suggested that student performance metrics contain clear patterns that effectively categorized into sentiment classes.
2. **Feature Importance**: In the research accordingly Feature selection determined that the correlation analysis indicated that PctProficient and ScaleScoreAvg were the most influential features in performance Sentiment.
3. **Grade-Level Patterns**: The grade- level patterns improved model performance, suggested significant variations in performance patterns across different educational stages of information.

ii. Practical Implications

1. **Early Intervention**: The Proposed model identified negative performance Sentiment early, enabling targeted interventions.
2. **Curriculum Evaluation**: A study help to Neutral sentiment results indicated areas where curriculum adjustments could improve outcomes.
3. **Policy Development**: The analysis provided quantitative support for evidence-based educational policymaking.

iii. Limitations and Future Work

1. **Data Scope**: The study used a specific assessment dataset and to generalization with other educational contexts requires validation.
2. **Temporal Aspects**: The current model didn't explicitly account for temporal trends in student performance.
3. **Future Enhancements**: The future enhancement may scope to Incorporation of additional contextual features (socioeconomic factors, school resources), Development of real-time monitoring systems, and Integration with natural language processing of qualitative feedback.

9. CONCLUSIONS

A study, reviewed the various noteworthy work related with Sentiment Analysis and Multiclass Sentiment Analysis (MCSA) used deep LSTM model. Firstly introduced the desired technological idea to performing Sentiment Analysis and Multiclass Sentiment Analysis. Then, kept aware about Sentiment Analysis methodology with reference to recent studies. Next explored the role of sentiment analysis and Multiclass Sentiment Analysis (MCSA) to insight on the text or documents to use in industry or institutes for enlargement to the business.Lastly the use of Sentiment Analysis and Multiclass Sentiment Analysis for educational institutes to enhancement of educational system like pedagogical concepts, decision making and evaluation process are shortly expressed in this article.Finally, this article gave an idea about incremental process of Sentiment Analysis and Multiclass Sentiment Analysis (MCSA) in case of educational institutions and other mentioned applications such as politics, Voice of Customer (VoC), Workforce analytics and voice of employees, digital marketing, Brand Monitoring, Social media monitoring and other.

This research successfully demonstrated the application of Multiclass Sentiment Analysis to student performance assessment data using LSTM neural networks. The developed model achieved near-perfect classification accuracy while provided interpretable insights into performance patterns. The methodology established a framework for educational Sentiment Analysis that adapted to various assessment systems. The findings had significant implications for educational practice, offered data-driven approaches to improve student outcomes and optimize teaching strategies.This comprehensive analysis provided both the technical details and educational insights necessary for a research paper on Multiclass Sentiment Analysis of student performance assessment data.Overall, in this paper, the Deep LSTM technological calculation incremental procedure roadmap for Sentiment Analysis and Multiclass Sentiment Analysis introduced shortly.

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