CHAPTER 5

RESULTS AND DISCUSSION

5.1 EXPERIMENTAL SETUP

This section discusses more information of the performance and effectiveness of the proposed system contribution. The results are implemented to evaluate the online twitter dataset with data processing simulation environment. The discussion starts with dataset and performance metrics and follows on to cover data collection and implementation. Relevant results are also discussed and presented for a better understanding. The projected implementation algorithm is tested with different classes of sentimental terms with our proposed system called DLMNN, and GBDT. The proposed feature classification has produced efficient results than other feature selection and classifiers such as ANN, k-means, DCNN. Then the evaluations of the proposed algorithm with different methodologies are discussed.

5.2 DATASET AND ENVIRONMENT SETUP

Twitter will not allow accessing its database directly however sample twitter data was collected from Twitter API and stored it in a local database. A computer with an Intel Core i5-7200 processor capable of running at 2.7GHz processing speed equipped with 8GB internal memory is used to perform the experiments. Windows 10, the 64-bit operating system is used to run the procedures by a dedicated User Interface (UI) and Jupyter Notebook (Python 3.7) Environment. Data cleaning and pre-processing was done by using Numpy and Pandas. Python software was used for relevant histogram drawings and graphical calculations. The proposed feature selection and classification algorithms have been implemented and tested for its efficiency in twitter dataset for positive and negative data examination. The application delivers sophisticated effectiveness associated with preceding examination circumstance consequences.

Table 5.1 Details of parameters

Parameters used	Values processed
Dataset used	Twitter Sentiment Corpus
Simulation environment	Python
Number of attributes	>=100
Number of class	3 (Positive, Negative, Neutral)

Table 5.1 shows the details of positive and negative sentimental dataset that are processed to test the presentation of the planned schemes.

5.3 PERFORMANCE ANALYSIS

Fundamentally, the presentation examination is completed by assessing the presentation metrics like a) Precision, b) Recall, c) F-score, d) classification accuracy, e) sentiment Score, f) time complexity. Presentation is grounded on evaluation metrics like classification accuracy, specificity-measure, time complexity and F-measure classification.

5.3.1 Classification Accuracy

Classification Accuracy Assessment is one of the most popular rating indicators. Accuracy is a performance gauge that denotes how closer the proposed system is to the target value. It is a gauge that ascertains the count of predictions that are made to the total count of predictions that are made. The system accuracy is computed utilizing the subsequent mathematical depiction. The Time Complexity is regarded as the amounts of time in which a CPU processes the instructions on a computer. This is a metric that possesses an imperative role in finding the proposed work's performances. The 'Average Sentiment Score' (ASS) is the mean value of the sentiment score. This value is an utmost precise numerical depiction of the sentiment's polarity.

5.3.2 Time Complexity

Time complexity is identified as the overall time taken to load the dataset to process the feature selection and classification in certain amount of time. The time complexity is calculated in milliseconds. The asymptotic Notation O (n), to express the top side, is the lower boundary at the time of instruction processing. With its time calculations and worst-case form, the average upper limit g(n) and the average mid limit f(n) calculate the difference as mean time that can probably measure the length of time that can be taken into account in full. The actual representation of this time complexity is measured by using the system configuration under 8GB of RAM with i5 Intel processor having python intent framework.

5.4 DLMNN-BASED SENTIMENT ANALYSIS ON TWITTER DATA

An efficient Feature selection method is required to select a small variety of features in a quick rate by preventing the measures high weights. The approach here follows the DLMNN and method for evaluation and producing a efficient feature selection with less running time. Also, the way towards recognizing and dismissing numerous unimportant and repetitive features. Extra features extremely influence the precision of the learning machines. In high dimensional space discovering, bunches of information objects are trying because of the reduction of dimensionality. At the point when the dimensionality builds, information in the redundant measurements may create much confusion. And furthermore, time complicated nature is the real issue in existing methodology. DLMNN aims at the selection of the most appropriate features and its classification.

With a specific end goal to correct these issues, our proposed techniques has made use of proficient feature subset selection in high dimensional information.

5.4.1 Precision Analysis

Table 5.2 Comparison of Precision Analysis - DLMNN

Impact of Precision in %			
Methods/no of data from datasets	**K-Means**	**DCNN**	**DLMNN**
100	89.13	89.01	89.88
200	88.63	89.94	90.71
300	87.59	90.87	91.91
400	88.06	90.65	93.33
500	90.10	91.30	95.78

The Table 5.2 shows the performance of the proposed and existing classifier in terms of precision value.

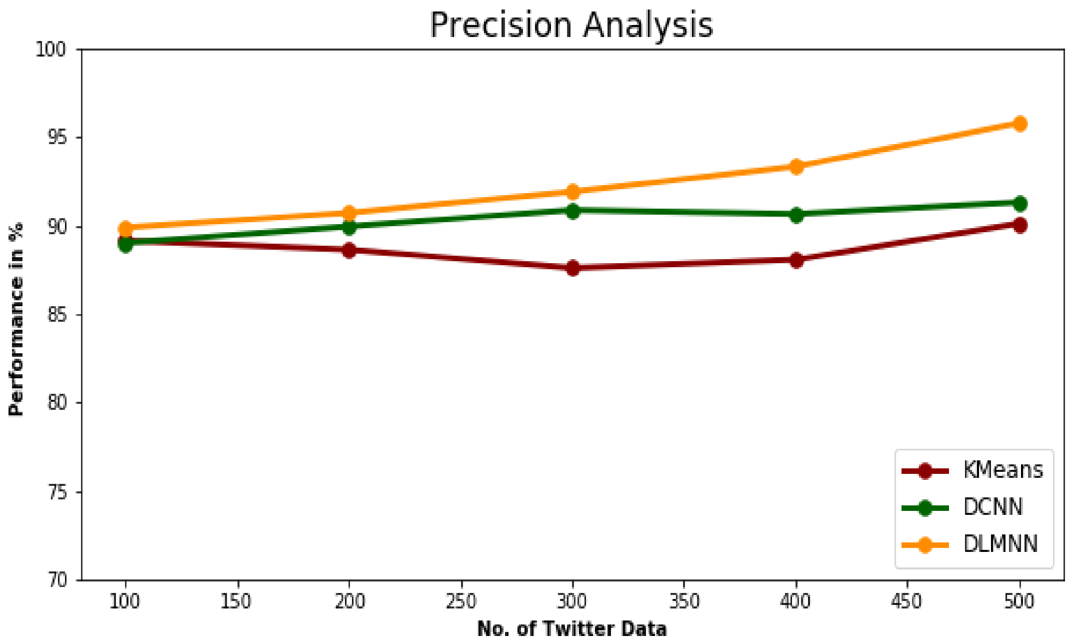

Figure 5.1 Comparison of Precision Analysis – DLMNN

Figure 5.1 shows the performance of the classifier and existing classifiers such as K-Means, DCNN and DLMNN in terms of Precision. The graph comparison proved that the performance in terms of precision, the proposed DLMNN attain the highest precision value of 95.78%. The precision value of existing K-Means, and DCNN is 90.10% and 91.30%, respectively when the data count is 500. These results are revealed that the proposed classifier recognizes the intruder's packets accurately compared to existing classifiers. The proposed method has proved to be more efficient than other methods.

5.4.2 Recall Analysis

Recall denotes the True Positive rate. This value is an imperative metric to ascertain the system’s performance. Here, the values of recall are computed for disparate values of data. The recall value increases as the data count increases.

Table 5.3 Comparison of Recall Analysis - DLMNN

Impact of recall analysis in %			
Methods/no of data from datasets	**K-Means**	**DCNN**	**DLMNN**
100	90.91	90.62	91.97
200	89.23	89.64	91.71
300	90.32	90.53	92.25
400	88.45	91.89	93.46
500	91.32	92.06	95.84

Table 5.3 demonstrates the contrast of recall analysis produced and it shows that the proposed model DLMNN produces higher performance ratio. In the prevailing K-Means, recall values are the least when the data count is 400. The recall decreases when 200 data are utilized and then it gradually rises as the data count increases. From Figure 5.2, it is perceived that the proposed DLMNN acquired better outcomes when weighed against the prevailing KMA and DCNN algorithm. The Recall performance varies based on the number of data. The data value starts from 100 and end with 500 data. When the data count is 200, the proposed DLMNN achieves above 91.71%, but the prevailing DCNN and KMA achieves below 90%. When the data count is 500, the proposed classifier DLMNN has obtained above 95.84% Recall but the existing DCNN and K-Means obtained below 93% Recall performance.

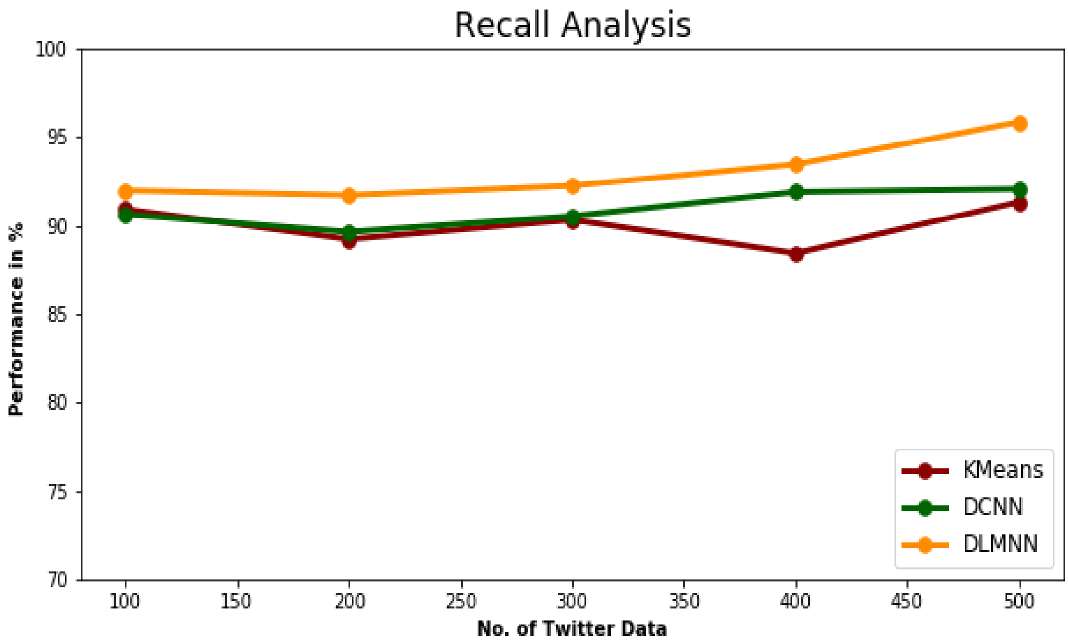

Figure 5.2 Comparison of Recall Analysis - DLMNN

Figure 5.2, shows the comparison of recall analysis produced by proposed and existing classification methods and the proposed method DLMNN has achieved higher performance rate than other existing methods.

5.4.3 F-Measure Analysis

The next performance gauge that is utilized for the comparative examination is the F-score. The F-score of this proposed DLMNN, K-Means and DCNN are calculated and compared. The attained F-score showed a stable increase as the data count increased. The K-Means witnessed an unequal increase and decrease on the value of F-score. This variation is elucidated using Figure 5.3.

Table 5.4 Comparison of F-Measure Analysis - DLMNN

Comparison of F-measure %			
Methods/dataset used	**K-Means**	**DCNN**	**DLMNN**
100	90.01	89.83	90.27
200	88.26	90.09	91.29
300	89.74	91.28	92.56
400	88.23	91.68	93.81
500	90.56	91.93	95.87

The present implementation search and actual references improve the tweet classification to textual information retrieval technology. Table 5.4 shows the comparison performances of F-measure proffered by the proposed DLMNN classifier and the prevailing DCNN and K-Means algorithms centered on F-Score measure. The F-Score performance varies based on the number of data. The data value starts from 100 and end with 500 data. When the data count is 200, the proposed DLMNN achieves above 91.29% F-score, but the prevailing DCNN and K-Means achieves 88.26% and 90.09% respectively. When the data count is 500, the proposed classifier has obtained above 95.87% F-score but the existing DCNN and K-Means obtained below 92% F-score performance. Similarly, the performance of the system varies for the remaining data counts. Thus, it is deduced that the proposed DLMNN proffers higher performance on considering the prevailing systems.

Figure 5.3 demonstrates the contrast of F-measure ratio performed by different methods and the projected method has formed less F-measure than other existing methods.

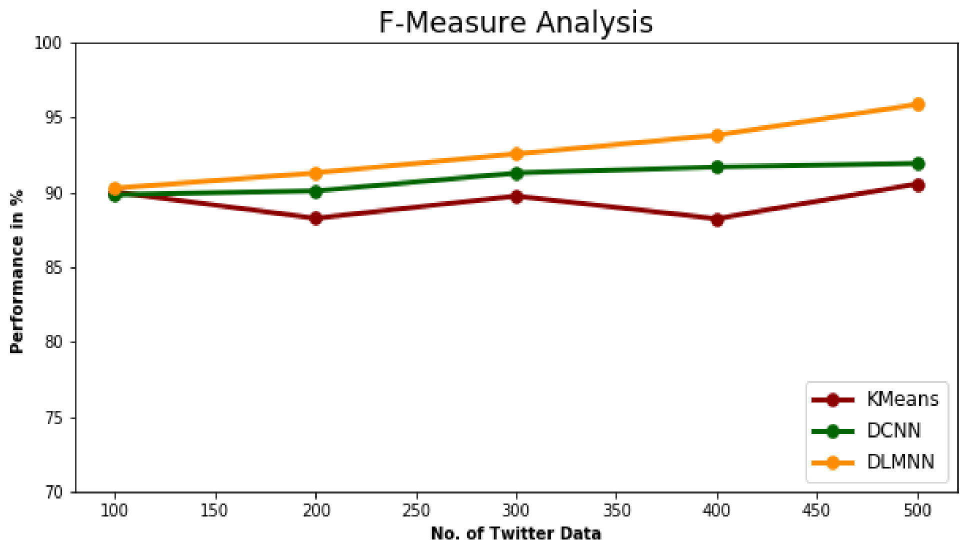

Figure 5.3 Comparison of F-measure - DLMNN

5.4.4 Classification Accuracy

Here the usual Conventional Neural Network is altered with the assistance of deep learning calculation. The order is performed utilizing Optimized Function neural network DLMNN system to group the smaller scale which exhibits information as typical or irregular information.

Table 5.5 Comparison of Classification Accuracy - DLMNN

Impact of Classification Accuracy in %			
Methods/no of data from datasets	**K-Means**	**DCNN**	**DLMNN**
100	82.13	81.12	83.12
200	80.50	82.23	84.56
300	80.33	83.47	86.78
400	79.51	84.65	88.62
500	83.62	85.71	91.65

Table 5.5, shows the comparison of classification accuracy produced by the proposed method compared to the existing methods on different datasets.

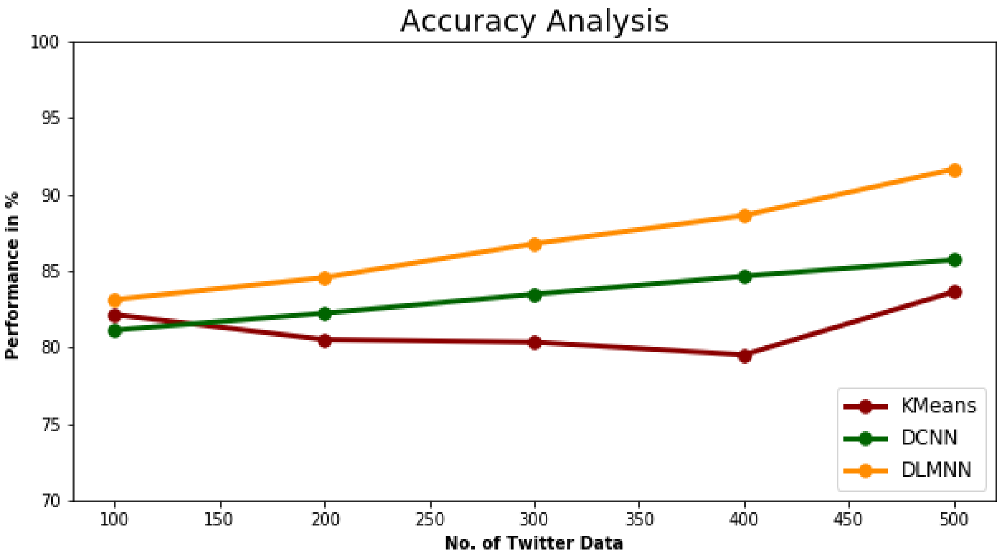

Figure 5.4 Comparison of Classification Accuracy - DLMNN

Figure 5.4 shows the comparison of classification accuracy, the DLMNN produced highest accuracy performance compared to the existing methods on different datasets.

5.4.5 Average Sentimental Score

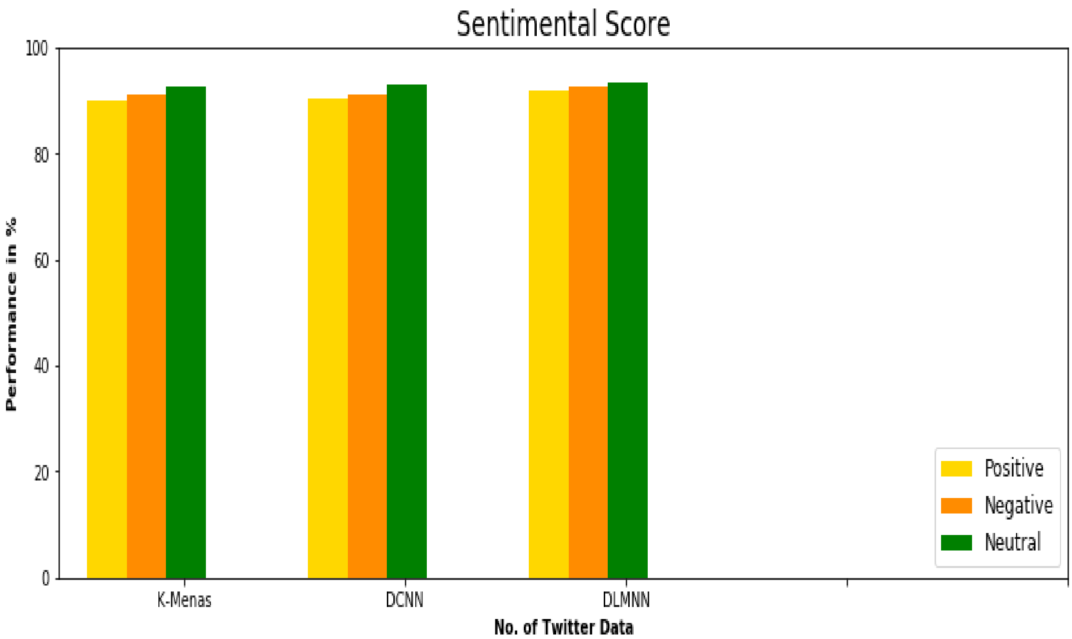

Figure 5.5 Sentimental Score comparison of K-Means, DCNN and DLMNN

In Figure 5.5 demonstrate the Comparison of proposed DLMNN sentiment score accuracy as positive negative, neutral classes. The proposed method has proved to be efficient sentiment classification and analysis in different point as well in datasets compared with existing methods

Table 5.6 comparison of Sentimental Score - DLMNN

Impact of sentimental score in %			
Methods/no of data from datasets	**Positive**	**Negative**	**Neutral**
K-Means	90.23	90.35	91.74
DCNN	91.15	91.18	92.56
DLMNN	92.61	92.91	93.29

In Table 5.6, Comparison of proposed sentiment score accuracy is done. The proposed method has proved to be efficient in different datasets compared with existing methods.

5.4.6 Time Complexity Analysis

Figure 5.6 shows that Time complexity analysis of Prevailing method K-Means, DCNN and proposed technique DLMNN. Time Complexity is measured milli seconds(ms). For training a classifier to analyze and execute the twitter data, the proposed DLMNN consumes 20.61 ms, 83.71ms, 238.02ms, 464.86ms and 1112.21ms for the data range N=100 to 500. Whereas DCNN consumes 22.11ms, 86.82ms, 256.23ms, 502.64ms and 1260.22ms for the data range N=100 to 500. K-Means technique required huge Time Complexity rather than DCNN and DLMNN. For an efficient classification, the classifier should be faster and accurate.

$$\text{Time complexity (Tc)} = \sum_{k=0}^{k=n} \times \frac{\text{total features handeled to process in dataset}}{\text{Time taken(Ts)}} \quad (5.1)$$

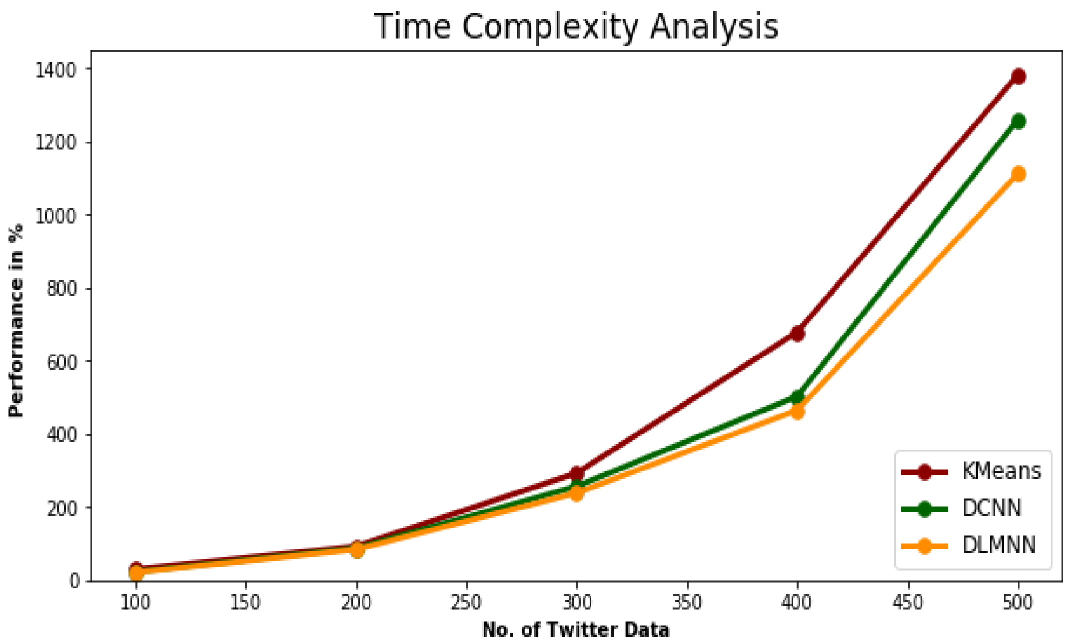

Figure 5.6 Comparison of Time Complexity - DLMNN

Figure 5.6 shows the comparison of time complexity produced by different methods and shows that the proposed approach DLMNN has produced minimum Time Complexity than other methods.

Table 5.7 Comparison of Time Complexity - DLMNN

Impact of Time complexity in milliseconds (ms)			
Methods/no. of data from datasets	**K-Means**	**DCNN**	**DLMNN**
100	29.51	22.11	20.61
200	92.11	86.82	83.71
300	292.46	256.23	238.02
400	678.45	502.64	464.86
500	1382.67	1260.22	1112.21

Above Table 5.7 reviews the time complexity comparisons of different methods and the proposed approach showing that least time required for sentiment analysis.

5.5 A GBDT BASED SENTIMENT CLASSIFICATION OF TWITTER DATA

The chosen features are assigned to the GBDT classifier as input. Gradient Boosting (GB) is the propitious ML methodology for regression along with classification problems. It creates a prediction framework in the sort of integration of weak prediction frameworks, mainly Decision Trees (DT). Similar to other boosting approaches, it stage-wise builds a model, and generalizes it by optimizing a random differentiable Loss Function (LF). The GB aims to attach new models to the ensemble successively. Beginning with operation, the data is also carried out using HDFS's Map Reduce. The relevant emoticon and non-emoticon features are extracted and are appropriately ranked centered on their characteristics. Here, a sub-set of features is selected as of the actual collection of features, which forms patterns in a considered dataset. It is done to lessen the size of the issue for learning algorithms, which might augment classification accuracy on account of a reduction in computational requisites. It elevates the classification speed as the data size to train the classifier is lessened. It is done utilizing the I-EHO technique.

Finally, the GBDT classifier classifies data as negative, positive, or neutral. Empirically, the proposed method is analyzed and distinguished using other conventional techniques to show the best performance.

5.5.1 Impact of Precision Analysis

In Figure 5.7 shows the comparison of Precision produced by First proposed model DLMNN and the second proposed model GBDT. It is observed from the graph that the precision increases as the number of data (N) increases in the case of both the proposed and the prevailing techniques. For N=100, the precision for the proposed GBDT is 90.09 and for N= 500, the precision for the proposed GBDT is 96.26, which is 6.0% greater for N= 100. Likewise, for all compared N values, the proposed GBDT proffered the highest performance.

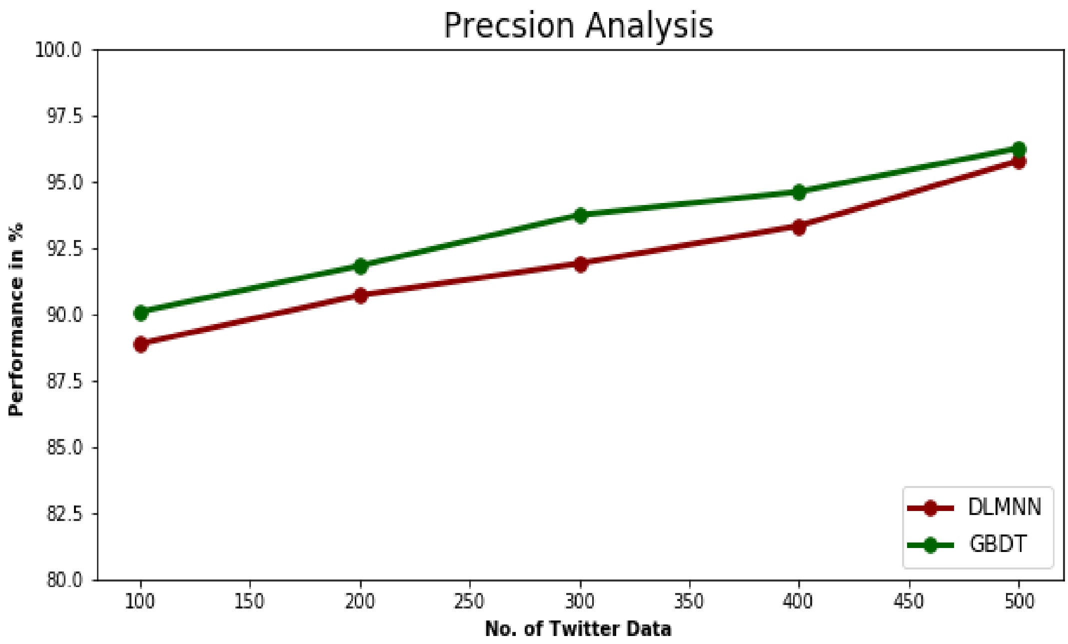

Figure 5.7 Performance Analysis of proposed GBDT and DLMNN in terms of Precision

Table 5.8 Comparison of Precision Analysis - GBDT

Impact of Precision in %		
Methods/no of data from datasets	**DLMNN**	**GBDT**
100	88.88	90.09
200	90.71	91.82
300	91.91	93.74
400	93.33	94.62
500	95.78	96.26

The above table 5.8 shows the comparison of prevailing model DLMNN and proposed GBDT technique in respect of precision for N=100,200,300,400 and 500.

5.5.2 Impact of Recall Analysis

Figure 5.8 analyzes the performances of the DLMNN and GBDT techniques in respect of Recall. The effectiveness of the proposed system classifier GBDT attain the recall value of 92.89%, 93.43%, 94.24%, 95.65% and 96.46% respectively. But the First proposed classifier achieves recall value of 91.97%, 91.71%, 92.25%, 93.46% and 95.84% respectively for N= 100, 200, 300, 400 and 500 data respectively. As the N values are increased further, the recall value is also augmented. For N= 500, the recall value for the proposed GBDT is 96.46%, which is greater on considering the prevailing DLMNN and in turn, it shows the greatest performance.

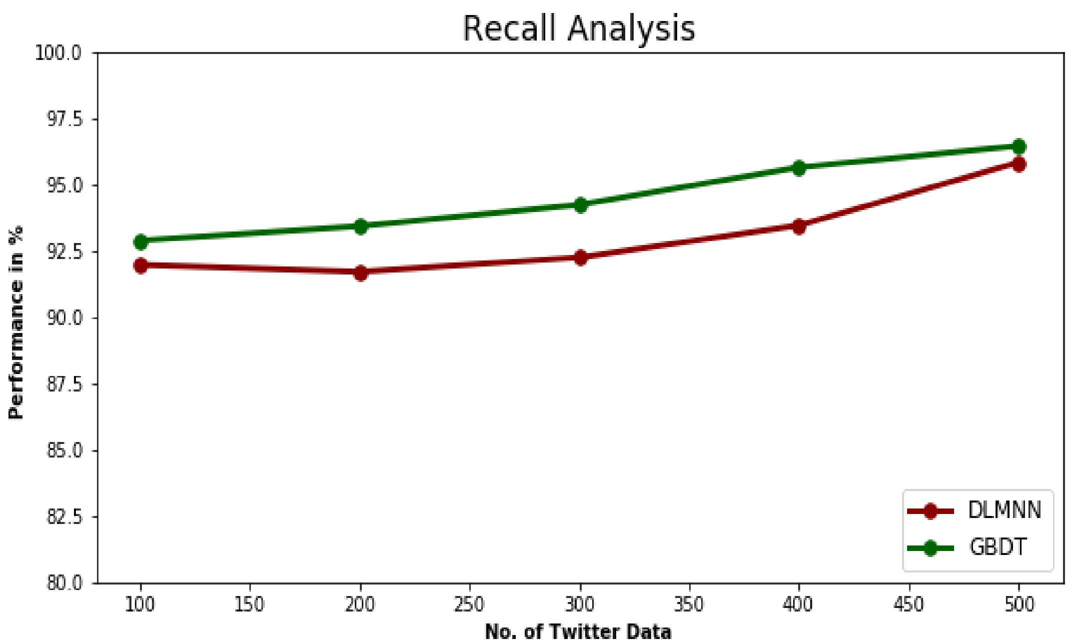

Figure 5.8 Performance Analysis of proposed GBDT and DLMNN in terms of Recall

Table 5.9 Comparison of Recall Analysis - GBDT

Impact of Recall Analysis in %		
Methods/no of data from datasets	**DLMNN**	**GBDT**
100	91.97	92.89
200	91.71	93.43
300	92.25	94.24
400	93.46	95.65
500	95.84	96.46

Table 5.9 shows the comparison of Recall analysis of DLMNN and GDBT and it shows that the proposed approach GBDT produces higher performance ratio.

5.5.3 Impact of F-Measure Analysis

Figure 5.9 analyzes the performances of the prevailing techniques DLMNN and proposed GBDT techniques in respect of F-Score. It is inferred that as the N value increases, the F-Score value also augments. For N= 100, F-Score value for the prevailing DLMNN is 90.27% and for N=500, F-Score value is 95.87% respectively. The proposed GBDT is 91.89%. For N= 100, and 96.36% f0r N=500. The proposed GBDT shows 96.36% F-Score value, which is greater on considering the prevailing techniques and in turn, it shows the greatest performance.

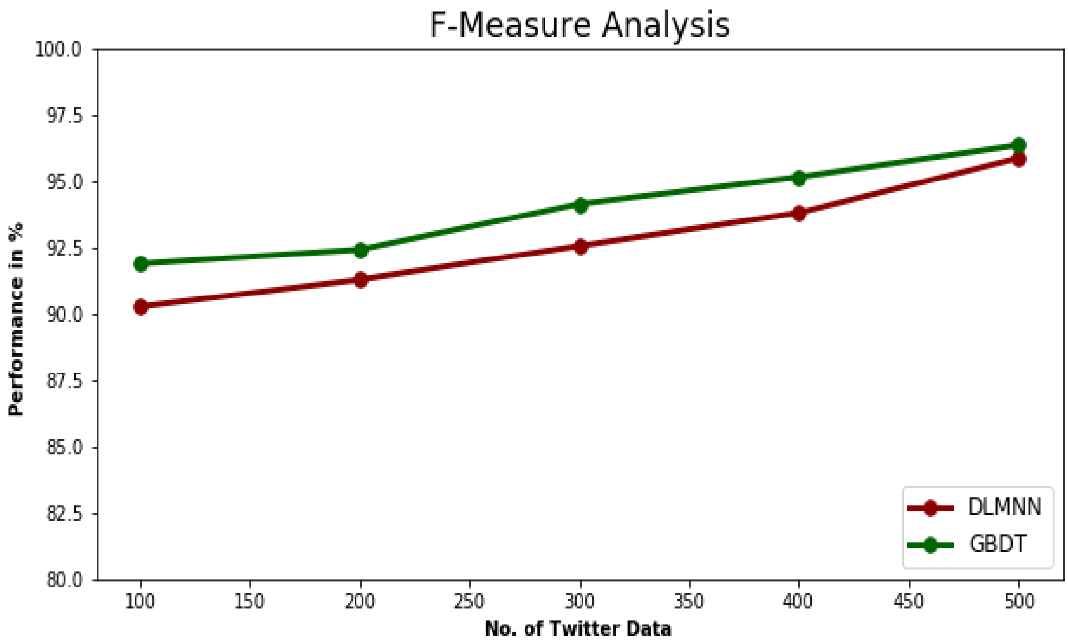

Figure 5.9 Performance Analysis of proposed GBDT and DLMNN in terms of F-Measure

Table 5.10 Comparison of F-Measure - GBDT

Comparison of F-measure in %		
Methods/dataset used	**DLMNN**	**GBDT**
100	90.27	91.89
200	91.29	92.42
300	92.56	94.14
400	93.81	95.16
500	95.87	96.36

Table 5.10 shows the comparison of F-measure ratio produced by DLMNN and GDBT methods.

5.5.4 Impact of Classification Accuracy

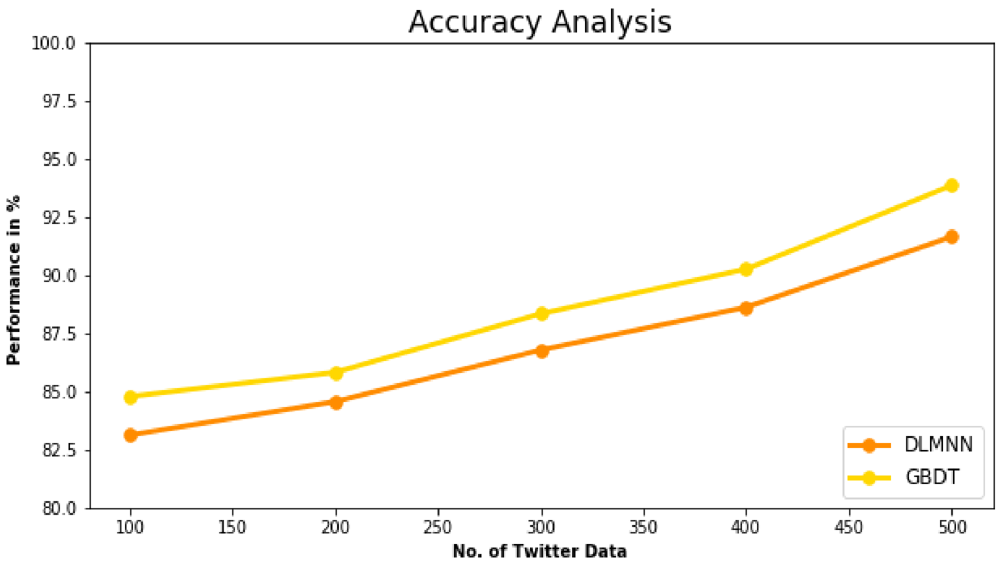

Figure 5.10 Performance Analysis of proposed GBDT and DLMNN in terms of Accuracy

Figure 5.10 shows the comparison of classification accuracy and shows that the second proposed method GBDT has produced higher classification accuracy than other methods. The test case results are evaluated through the experimentation carried out using five dissimilar micro array dataset using GBDT classifiers. This performs the higher efficient result compared to the previous existing results that produce 93.86% accuracy in Twitter data whereas GBDT produces 91.65% accuracy. The GBDT classifier holds the feature subset evaluation of higher accuracy than other methods.

Table 5.11 Comparison of Classification Accuracy

Impact of classification accuracy in %		
Methods/no of data from datasets	**DLMNN**	**GBDT**
100	83.12	84.78
200	84.56	85.82
300	86.78	88.34
400	88.62	90.26
500	91.65	93.86

Table 5.11 shows that the classification accuracy comparison value of DLMNN and GBDT for N=100 to 500 data range.

5.5.5 Average Sentimental Score Analysis

Figure 5.11 analyzes the performance of prevailing method DLMNN and second proposed GBDT technique in respect of sentiment sore. It is observed from the graph that GBDT has the highest sentiment analysis score than DLMNN. GBDT achieved 93.0% (Positive), 93.95% (Negative) and 94.56 (Neutral) score.

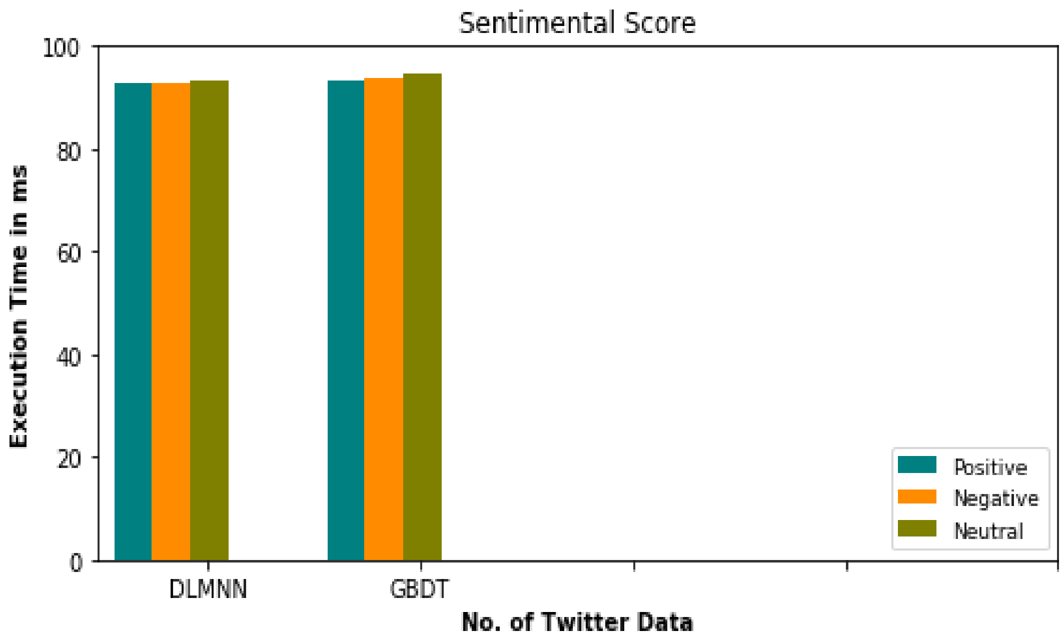

Figure 5.11 Sentimental Score Comparison of DLMNN & GBDT

Figure 5.11, shows the sentimental score performed by the projected method GBDT compared to the existing method DLMNN.

Table 5.12 Comparison of Sentimental Score - GBDT

Impact of sentimental score in %			
Methods/No. of data from datasets	**positive**	**Negative**	**Neutral**
DLMNN	92.61	92.91	93.29
GBDT	93.07	93.95	94.56

Table 5.12, demonstrates the assessment of sentimental score performed by the projected method compared to the existing methods on different datasets. In the end of research, it is found that the methods involved in the dictionary are best used in some cases where human-labeled documents are very effective, which require some effort.

5.5.6 Impact of Time Complexity Analysis

Figure 5.12 shows that Time complexity analysis of Prevailing method DLMNN and proposed technique GBDT. Time Complexity is measured milli seconds(ms). For training a classifier to analyze and execute the twitter data, the proposed GBDT consumes 37.91ms, 40.11ms, 44.89ms, 51.68ms, and 56.17ms for the data range N=100 to 500. Where as DLMNN consumes 40.61ms, 46.71ms, 51.22ms, 58.86ms and 63.21ms for the data range N=100 to 500. For an efficient classification, the classifier should be faster and accurate.

$$\text{Time complexity (Tc)} = \sum_{k=0}^{k=n} \times \frac{\text{total features handeled to process in dataset}}{\text{Time taken(Ts)}} \qquad (5.2)$$

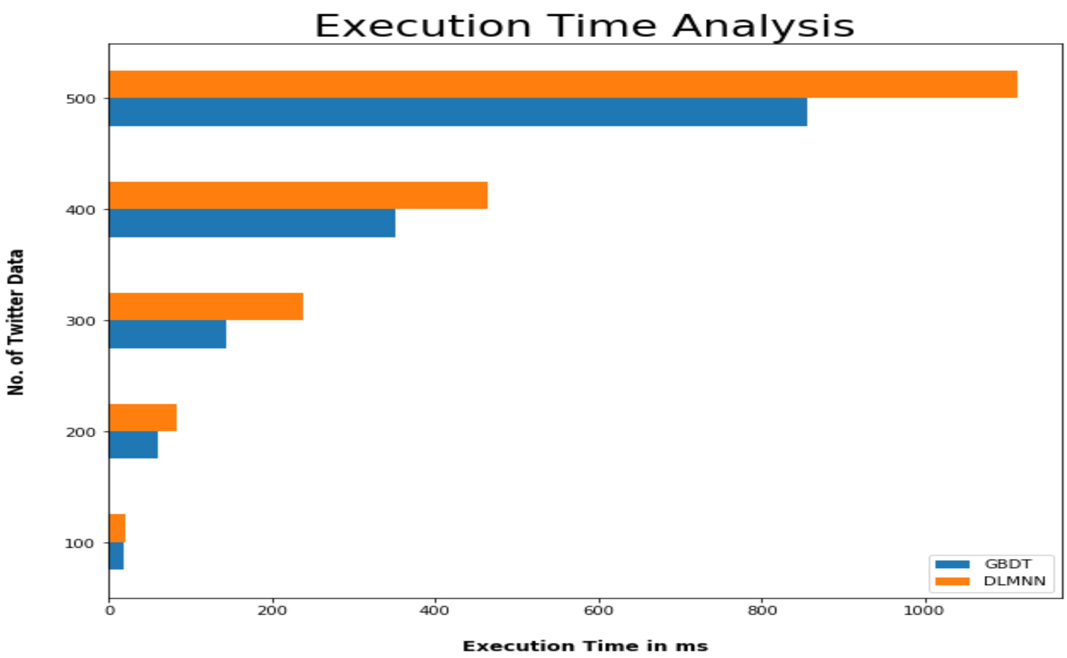

Figure 5.12 Performance Analysis of proposed GBDT and DLMNN in terms of Time Complexity

Table 5.13 Comparison of Time Complexity

Impact of time complexity in milliseconds (ms)		
Methods/no of data from datasets	**DLMNN**	**GBDT**
100	20.61	18.91
200	83.71	60.11
300	238.02	144.89
400	464.86	351.68
500	1112.21	856.17

Table 5.13 Shows the comparisons of GBDT and DLMNN time complexity for analyzing the twitter data in milli seconds.

From all the experimental result, it is clear that the proposed classifier GBDT is highly efficient and accurate. At the end of research, it is found that the GBDT methods involved in the tweet feature selection and classification are best used in some cases, where human-labeled documents analysis based on sentiment analysis are very effective, which require some effort.

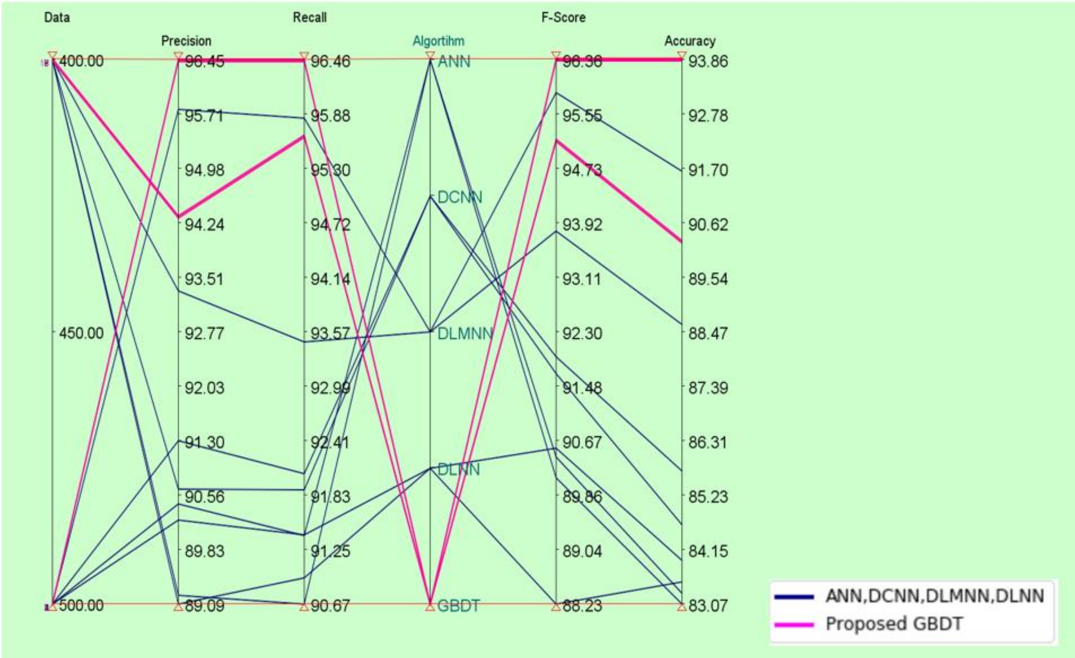

Figure 5.13 Performance Analysis of proposed GBDT and Existing models in terms of Precision, Recall, F-Score and Accuracy

Figure 5.13 analyzes the performances of the prevailing techniques DLMNN and proposed GBDT techniques in respect of Precision, Recall, F-Score and Accuracy. The proposed GBDT achieved 96.45% (Precision),96.46% (Recall), 96.36% (F-Score)and 93.86%(Accuracy) For N= 500, and 94.33% (Precision), 95.65% (Recall), 95.16% (F-Score)and 90.26%(Accuracy) N=400. The proposed GBDT shows 93.86% Accuracy, which is greater on considering the prevailing techniques and in turn, it shows the greatest performance. Comparing the above experiment results in existing and proposed model we can conclude that the proposed GBDT shows better performance than ANN,DCNN,DLMNN and DLNN algorithms with atmost accuracy.

5.6 SUMMARY

The chapter summarized the resultant and its performance of the proposed GBDT methods compared with existing methods. An Efficient Sentimental Analysis and Sentimental Classification of Twitter data are proposed by using GBDT classifier. The performance presented with the projected GBDT and existing DCNN and DLMNN methods are evaluated and contrasted in respect of metrics namely Precision, Recall, F-Score, Accuracy, Average sentiment score and Time Complexity. The experimental results imply that the proposed Sentimental Analysis technique using Twitter information is an extremely proficient methodology in the Big Data. It's analyzed from the results that the performance metrics worth rises as the number of data (N) fortify in the event of the proposed and also the prevailing techniques. It is concluded that the proposed GBDT result proves superior result, higher efficiency and performance compared to existing techniques.