MEASURING PERFORMANCE OF SVM,KNN,HYBRID AND ANN(MLP) ON BASIS OF ACCURACY AND PRECISION

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***Abstract*:** Tweets pre-process and extract unigram features after pre-processing of the tweets. In pre-processing, the noisy data is removed by using tokenization; stop word removal and stemming these processes remove the duplicate data like to repeat words, hash tags and emojis. These features and label learn by KNN, SVM and a hybrid of KNN and SVM. In thesis work, the proposed approach uses artificial neural network which gets improved by Multilayer perceptron (ANN-MLP or MLP-ANN). The proposed approach involves a nonlinear mapping of features and refined results by hidden layer. The experimental analysis shows that ANN-MLP improves all metrics like precision, recall and accuracy. So, it further indicates that the proposed approach improves the tweet sentiment classification results under 5-cross validation and 10-cross validation.

***Index Terms* - ANN, MLP, tweets, sentiments, KNN.**

I. INTRODUCTION

1.1. Artificial Intelligence

Artificial intelligence's progress is staggering. Efforts to advance AI concepts over the past 20 years have resulted in some truly amazing innovations. Big data, medical research, and autonomous vehicles are just some of the incredible applications emerging from AI development. According to the father of Artificial Intelligence, John McCarthy, it is "The science and engineering of making intelligent machines, especially intelligent computer programs". Artificial Intelligence is a way of making a computer, a computer-controlled robot, or a software think intelligently, in the similar manner the intelligent humans think. AI is accomplished by studying how human brain thinks, and how humans learn, decide, and work while trying to solve a problem, and then using the outcomes of this study as a basis of developing intelligent software and systems [4, 15].

1.1.1 Goals of AI

(1) To Create Expert Systems: The systems which exhibit intelligent behaviour, learn, demonstrate, explain, and advice its users.
(2) To Implement Human Intelligence in Machines: Creating systems that understand, think, learn, and behave like humans.

1.2 Natural Language Processing

NLP is a way for computers to analyze, understand, and derive meaning from human language in a smart and useful way. By utilizing NLP, developers can organize and structure knowledge to perform tasks such as automatic summarization, translation, named entity recognition, relationship extraction, sentiment analysis, speech recognition, and topic segmentation [5] [14]. NLP considers the hierarchical structure of language: several words make a phrase, several phrases make a sentence and, ultimately, sentences convey ideas," John Rehling, an NLP expert at Meltwater Group, said in. "By analysing language for its meaning, NLP systems have long filled useful roles, such as correcting grammar, converting speech to text and automatically translating between languages. This human-computer interaction enables real-world applications like, and more.

1.2.1 Applications of NLP

Natural Language Processing is the driving force behind the following common applications:

- Language translation applications such as Google Translate.
- Word Processors such as Microsoft Word and Grammarless that employ NLP to check grammatical accuracy of texts.
- Interactive Voice Response (IVR) applications used in call centers to respond to certain users' requests.
- Personal assistant applications such as OK Google, Siri, Cortana, and Alexa.

1.3 Social Media Analysis

First step in social media analytics process is extracting business relevant data. Broadly, data extraction could have 2 different scopes. For requirements such as brand or campaign monitoring, the scope is all posts from entire social media universe that match to a *defined set of keywords or search terms.*

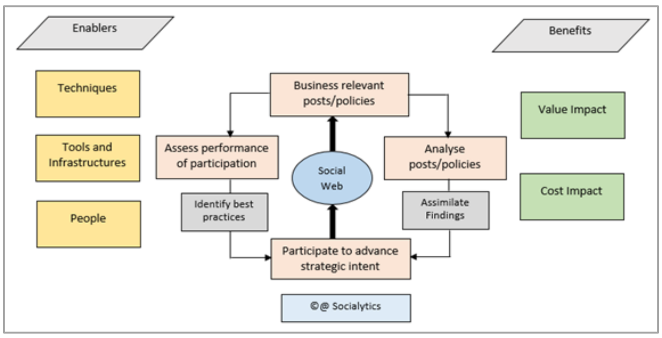

Fig. 1: Social media analytics

On the other hand, for requirements such as performance measurement or competitive intelligence, the scope is all posts from *a defined set of social media profiles*. After extraction comes the ANALYZE step where we try to clean and make sense of the gathered data. This may involve aspects such as volume trend analysis, ranking posts, ranking profiles, etc. EXTRACT and ANALYZE steps performed on a regular basis constitutes a social media listening program. The findings and insights from a listening exercise could feed into various business functions such as product development, customer support, sales, etc. as depicted in the social analytics life cycle defined by Ken Burbary and Chuck Hemann [7][8, 10].

II. SENTIMENT ANALYSIS

The concept of sentiment analysis is understood by combining the terms "Senitiment" and "Analysis". The word sentiment represents feeling that can be joyful, confusing, irritating, distracting. The sentiments are the feelings based on certain attitudes and opinions rather than facts due to which sentiments are of subjective nature [2] [6]. The sentiment implies an emotion usually motivated by opinion or perception of a person. The psychologists attempts to present multitude of emotions classified into six distinct classes: joy, love, fear, sadness, surprise and anger. The emotions based on sadness and joy are experienced on daily basis at different levels. We are mainly concerned about sentiment analysis detecting a positive or a negative response or opinion [1][2]. The major significance of sentiment analysis is that every emotion is linked to human perception forming an ingrained part of all humans which means that every human has the potential to generate different opinions acting as a tool for sentiment analaysis. Sentiment analysis refers to the analysis automation of a known text determining the distinct types of feelings conveyed. The term sentiment analysis and opinion mining can be used interchangeably [3][7].

2.1 Need for sentiment analysis

In today's environment where we're justifiably suffering from data overload (although this does not mean better or deeper insights), companies might have mountains of customer feedback collected; but for mere humans, it's still impossible to analyse it manually without any sort of error or bias [9, 11]. Oftentimes, companies with the best intentions find themselves in an *insights vacuum*. You

know you need insights to inform your decision making and you know that you're lacking them, but don't know *how* best to get them. Sentiment analysis provides some answers into what the most important issues are, from the perspective of customers, at least. Because the sentiment analysis can be automated, and therefore decisions can be made based on a significant amount of data rather than plain intuition that isn't always right.

2.2 Working of Sentiment Analysis

Sentiment analysis is often driven by an algorithm, scoring the words used along with voice inflections that can indicate a person's underlying feelings about the topic of a discussion. Sentiment analysis allows for a more objective interpretation of factors that are otherwise difficult to measure or typically measured subjectively, such as:

- The amount of stress or frustration in a customer's voice.
- How fast the individual is speaking (rate of speech).
- Changes in the level of stress indicated by the person's speech (such as in response to a solution provided by a customer support representative).

In customer service and call centre applications, sentiment analysis is a valuable tool for monitoring opinions and emotions among various customer segments, such as customers interacting with a certain group of representatives, during shifts, customers calling regarding a specific issue, product or service lines, and other distinct groups. Sentiment analysis may be fully automated, based entirely on human analysis, or some combination of the two. In some cases, sentiment analysis is primarily automated with a level of human oversight that fuels machine learning and helps to refine algorithms and processes, particularly in the early stages of implementation [5][14].

2.3 Approaches for Sentiment Analysis

There are three basic approaches of Sentiment Analysis [5][14]:

1. Machine learning based approach: It uses classification technique to classify text; it consists of two sets of documents: training and a test set. The training set is used for learning the differentiating characteristics of a document, while the test set is used for checking how well the classifier performs.
2. The lexicon based approach: It uses sentiment dictionary with opinion words and match them with the data for determining polarity. There are three techniques to construct a sentiment lexicon: manual construction, corpus-based methods and dictionary-based methods. The manual construction is a difficult and time-consuming task. Corpus-based methods can produce opinion words with relatively high accuracy. Finally, in the dictionary based techniques, the idea is to first collect a small set of opinion words manually with known orientations, and then to grow this set by searching in the WordNet dictionary for their synonyms and antonyms.
3. Hybrid Approach: Finally, in the hybrid approach, the combination of both the machine learning and the lexicon based approaches has the potential to improve the sentiment classification performance.

2.4 Applications of sentiment analysis

Sentiment analysis tools can be used by organizations for a variety of applications, including:

- Identifying brand awareness,reputation and popularity at a specific moment or over time.
- Tracking consumer reception of new products or features.
- Evaluating the success of a marketing campaign.
- Pinpointing the target audience or demographics.
- Collecting customer feedback from social media, websites or online forms.
- Conducting market research.
- Categorizing customer service requests.

III. RELATED WORK

Nicholas Cummins, et.al [1] explained the advantages of using cross domain data when performing text-based sentiment analysis have been established; however, similar findings have yet to be observed when performing multimodal sentiment analysis. A potential reason for this is that systems based on feature extracted from speech and facial features are susceptible to confounding effecting caused by different recording conditions associated with data collected in different locations. In this regard, the experts herein explored different Bag-of-Words paradigms to aid sentiment detection by providing training material from an additional dataset. Key results presented indicate that using a Bag-of-Words extraction paradigm that takes into account information from both the test domain and the out of domain datasets yields gains in system performance.

Yujiao Li, et.al [2] studied public emotion and opinion concerning the opening of new IKEA stores, specifically, how much attention are attracted, how much positive and negative emotion are aroused, what IKEA-related topics are talked due to this event. Emotion is difficult to measure in retail due to data availability and limited quantitative tools. Twitter texts, written by the public to express their opinion concerning this event, are used as a suitable data source to implement sentiment analysis. Around IKEA opening days, local people post IKEA related tweets to express their emotion and opinions on that. Such “IKEA” contained tweets are collected for opinion mining in this work.

Sahar Sohangir, et.al [3] explained that the Multi layer Preceptrons can overcome data mining approach in stock sentiment analysis. In standard data mining approach to text categorization, documents represent as bag-of-word vectors. These vectors represent which words appear in a document but do not consider the order of the words in a sentence. It is clear that in some cases, the word order can change the sentiment of a sentence. One remedy to this problem is using bi-grams or n-gram in addition to uni-gram. Unfortunately, using n-grams with n > 1 was not effective. Using MLP provides this opportunity to use n-grams to extract the sentiment of a document effectively.

Nick Jennings, et.al [4] explored how humans and AI systems can work together. In such partnerships, the humans and the AI systems complement each other's strengths and weaknesses, leading to a rise in the humans, as well as in the machines. Drawing on multi-disciplinary work in the areas of AI, autonomous systems, machine learning, crowd sourcing and ubiquitous computing, this talk explores the scientific underpinning of such systems, the applications they have been applied to, and the societal implications of their widespread adoption.

Rajkumar S. Jagdale, et.al [5] elaborated different approaches of Sentiment Analysis and Opinion Mining for different dataset and find out which approach is best for which dataset which will help to researchers to select approach and dataset. In proposed work we collected tweets using R tool of different events from twitter and did pre-processing and calculate sentiment score from that events. We plot Wordcloud of particular event which highlight the frequent term from tweets and also calculated numbers of positive, negative and neutral tweets from each events.

Aishwarya Kotwal, et.al [6] explained that Twitter represents a microblogging site where people post and read views about various topics. These tweets contain people’s opinion, emotions, sentiments, appraisals, evaluations regarding entities consisting of movies, politics, research, business, sports etc. This data can be obtained by using Twitter API services. The sentiments of this collected data can be studied, analyzed and categorized as positive, negative or neutral. Thus the popularity of the topic can be detected from the statistics of the opinions and emotions which is achieved by classifying the data to the trained form. The size of the data obtained from the twitter is humungous. To handle such data the Hadoop framework is used to store, process and manage it so that it can be time efficient.

Harsh Thakkar, et.al [7] represented Open social networks as the best examples of sociological trust. The exchange of messages, followers and friends and varying sentiments of users provide a crude platform to study behavioural trust in sentiment analysis domain. Machine learning approaches have been so far good in delivering accurate results. Depending upon the application, the success of any approach will vary. Lexical approach is a ready-to-go and doesn’t require any prior information or training. While on the other hand machine learning requires a well-designed classifier, huge amount of training data sets and performance tuning prior to deployment. Hybrid approach has so far displayed positive sentiment as far as performance is concerned.

Bogdan Batrinca, et.al [8] presented a study to analyze the wealth of social media now available. It presents a comprehensive review of software tools for social networking media, wikis, really simple syndication feeds, blogs, newsgroups, chat and news feeds. For completeness, it also includes introductions to social media scraping, storage, data cleaning and sentiment analysis. Although principally a review, the paper also provides a methodology and a critique of social media tools.

Supriya B. Moralwar, et.al [9] explained that the mechanism of Sentiment analysis is also known as opinion mining or opinion extraction. Sentiment analysis is helpful indifferent field for calculating, identifying and expressing sentiment. This paper illustrates the research area of Sentiment Analysis on reviews on product like amazons, android apps and its latest advances. It affirms the levels of sentiment classification, data source for review collection, and Approaches for sentiment classification. Most work has been done on product reviews downloaded from Amazon.

Roosevelt C. Mosley, et.al [10] discussed the application of correlation, clustering, and association analyses to social media. This is demonstrated by analyzing insurance Twitter posts. The results of these analyses help identify keywords and concepts in the social media data, and can facilitate the application of this information by insurers. As insurers analyze this information and apply the results of the analysis in relevant areas, they will be able to proactively address potential market and customer issues more effectively.

Huifeng Tang, et.al [11] discussed four problems, i.e., subjectivity classification, word sentiment classification, document sentiment classification based on machine learning techniques, and opinion extraction problem. Although we were able to obtain fairly good results for the review classification task through the choice of appropriate features and metrics, but we identified a number of issues that make this problem difficult.

Robert Malouf, et.al [12] suggested that social network analysis is an important tool for performing natural language processing tasks with informal web texts. A database of postings from a US political discussion site was collected, along with self-reported political orientation data for the users. A variety of sentiment analysis, text classification, and social network analysis methods were applied to the postings and evaluated against the users' self-descriptions.

Scott S. Piao, et.al [13] proposed a system which is based on existing semantic lexical resources and NLP tools, aiming to create a network of opinion polarity relations between documents and citations. This is a web-based system which allows users to access the citations collected from documents and retrieve those documents linked to each of the citations with different opinion polarity relations, namely approval, neutral or disapproval relations. Various approaches will be tested including detecting semantic orientation of subjective words in the context of citations and machine learning using manually annotated data.

IV. THE PROPOSED METHOD

4.1 Proposed Methodology

Proposed steps followed to achieve results:

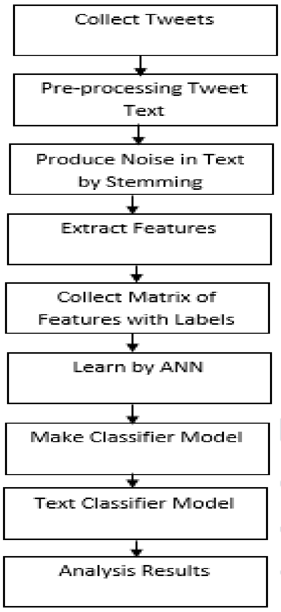

Fig.2: Proposed Steps

4.2 Proposed methodology: Flowchart

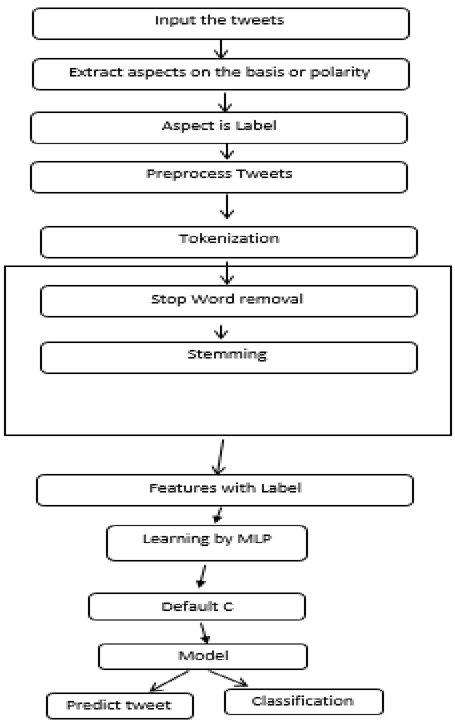

Fig.3: Proposed Flowchart

V. RESULT ANALYSIS

5.1 Platform used

Multi-layer Perceptron's (MLP), were first introduced by Yann LeCun's in 1998 for Optical Character Recognition (OCR), where they have shown impressive performance on character recognition. MLP is not just used for image related tasks, they are also commonly used for signals and language recognition, audio spectrograms, video, and volumetric images.

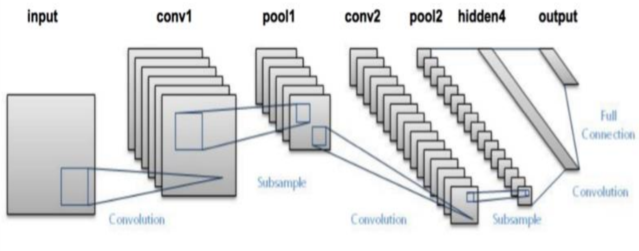

Fig.4: MLP uses multiple layers in its architecture.

Following are the layers used to build Multi-layer Preceptron architectures.
1. Multilayer Preceptrons (MLP): MLP is not just used for image related tasks, they are also commonly used for signals and language recognition, audio spectrograms, video, and volumetric images.
2. Convolutional Layer: Convolution Layer provides a convolution operation, in which a 2-D or 3-D filter of appropriate size sweeps over an image and apply the filters to each depth of an image. The convolutional layers are restricted version of the Multi-Layer Perceptron (MLP) adapted to take a 2D / 3D inputs instead of 1D. The idea behind convolutional layers is to detect elementary features such as edges, corners, and endpoints, and combine them using multiple layers to get high-level features that might describe an object completely.
3. Pooling Layer: Pooling is a method of reducing the feature size in width and height of an input. The pooling operation sweeps a rectangular window over the input feature and computes a size reduction operation for each window (average, max, or max with arg max).
4. Fully Connected Layer: Fully-connected layers refer to be the final layers in the full MLP model. It is the called as dense layer, where each neuron in one layer is connected to each and every neuron in the following layer.
5. Activation Function: The activation function is really important to the deep neural network, which is complicated and complex. They bring non-linearity property to neural networks.
6. Strides**:** Stride is a concept, which controls the movement the kernel over an image in convolution and max pool operation.
7. Padding: Padding the input image is 3D or 2D with zeros, such that the convolution layer does not alter the spatial dimensions of the input image. With the zero padding while convolution controls the spatial size of the output image from convolution layer.

5.2 Implementation Detail
Step1: Data Collection
Step2: Storing and fetching the data
Step3: Data Pre-processing
Step4: Applying various mining techniques
Step5: Result optimization

5.3 Result Analysis

5.3.1 Confusion Matrix

A confusion matrix (Kohavi and Provost, 1998) contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. The following table shows the confusion matrix for a two class classifier.

The entries in the confusion matrix have the following meaning in the context of our study:

- *a* is the number of **correct** predictions that an instance is **negative**,
- *b* is the number of **incorrect** predictions that an instance is **positive**,
- *c* is the number of **incorrect** of predictions that an instance **negative**, and
- *d* is the number of **correct** predictions that an instance is **positive**.

Table 1 Accuracy based on positive and negative

ACTUAL/PREDICTED	NEGATIVE	POSITIVE
NEGATIVE	a	b
POSITIVE	c	d

5.5.3 Results

Result Analysis

This part includes the details of the experiment on the basis of different classifiers as represented below:

Table 2 Accuracy of SVM, KNN, Hybrid, and MLP (ANN) classifiers

No of Validation	SVM (Accuracy)	KNN(Accuracy)	Hybrid (Accuracy)	MLP(ANN)(ACCURACY)
five-Fold	52	49.23	72.13	88.34
ten-Fold	54.34	51.23	75.67	90.34

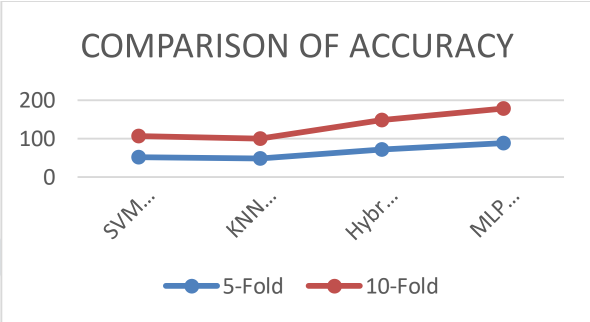

Fig. 4: Accuracy of SVM, KNN, Hybrid, and MLP (ANN) classifiers

In figure 4 it depicts the accuracy of the different classifiers that are existing and MLP (ANN). The X-axis on graph represents the validation fold and Y-axis represents the values of accuracy. The hybrid algorithm shows the maximum accuracy in 5-fold and 10-fold validation testing process. The minimum accuracy 49.23 is shown by KNN in 5-fold validation process. In proposed approach use of Multi-Layer Perceptron in ANN which improved the classification accuracy 90.34%

Table 3 Precision on SVM, KNN, Hybrid, and MLP (ANN) classifiers

No of Validation	SVM (Precision)	KNN(Precision)	Hybrid (Precision)	MLP(ANN)(precison)
five-Fold	62	50.23	81.13	87.34
Ten-Fold	63.23	51.23	82.23	88.96

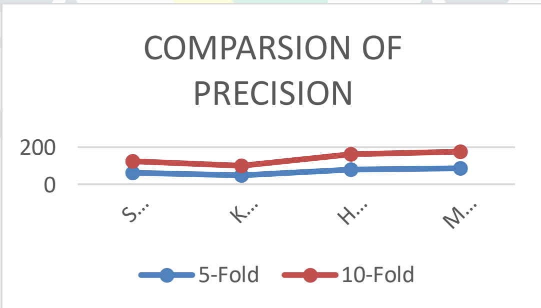

Fig. 5: Precision on SVM, KNN, Hybrid, and MLP (ANN) classifiers

In figure 5 it depicts the Precision of the different classifiers that are existing and MLP (ANN). The X-axis on graph represents the validation fold and Y-axis represents the values of Precision. The hybrid algorithm shows the maximum Precision in 5-fold and 10-fold validation testing process. The minimum Precision 50.23 is shown by KNN in 5-fold validation process. In propose approach use Multi-Layer Perceptron in ANN which improve the classification accuracy 88.96%

Accuracy improves the true positive and true negative which significantly improves the accuracy and reduces the error. Precision and Recall directly show the impact on the true positive and true negative on errors. If it increases then its significance reduces the error. If it reduces then it increases the error. F-measure is the average of precision and recall. In propose approach use Multi-Layer Perceptron in ANN which improve the classification parameters 8-10%

Table 4 Comparison values of SVM, KNN, Hybrid, and MLP (ANN) classifiers

No of Validation	SVM (Accuracy)	KNN(Accuracy)	Hybrid (Accuracy)	MLP(ANN)(ACCURACY)
five-Fold	52	49.23	72.13	88.34
ten-Fold	54.34	51.23	75.67	90.34

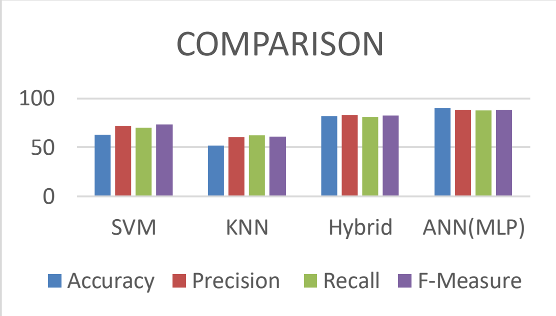

Fig. 6: Comparison of SVM, KNN, Hybrid, and ANN (MLP) classifiers

In figure 6 it depicts the comparison of the different classifiers that are SVM, KNN, Hybrid, and ANN(MLP). The X-axis on graph represents the classifiers and Y-axis represents the values of Accuracy, Precision, Recall and F-measure. The hybrid algorithm shows the maximum results on all parameters and KNN shows the minimum result among all. In this analysis show the impact of MLP-ANN improvement on tweets sentiment classification. The experimental results shows that the classification model made by MLP-ANN improves accuracy, precision and recall as compared to other machine learning approaches such as existing . Here, are following reasons behind this improvement.

- Nonlinear mapping of features which is helpful in increasing the domain knowledge of features.
- Refinement of learning methods by hidden layers and the use of sigmoid activation function in ANN.

VI. CONCLUSION

In this study, the concept of Support Vector Machines (SVM) is used for classification of algorithm with binary classification process. Such type of method helps in analyzing different feature vectors with an assigned class in order to identify the relation dependency between a sentiment and each of the feature. Here, each of the vector is considered as a point of data in vector dimensional space that equals to the size of feature-set. The SVM helps in identifying the vector dimension based hyperplane which divides the class into two types. One is the considered as "best" i.e. defined as a good type of separation gained by the hyperplane having the large distance to the point nearest to the training data type of any kind of class known as functional margin. In general, if the margin is large then the classifier error gets reduced. When the new form of tweet i.e. unlabeled is fed into the system.In the experimental analysis, MLP with ANN indicates an effective precision and accuracy than the other approaches. In case of improvement analysis, the proposed (MLP-ANN) approach using hidden layer is useful in improving the features of tweets text and MLP nonlinear mapping of features. These type of characteristics are supportive in improving the accuracy, precision and recall. The improvement analysis obtained is 8-10% on 10-cross validation and 4-5% in 5-cross validation. So, it concludes that ANN-MLP improves the performance of sentiment analysis as compared to other machine learning approaches.

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