High Performing Sentiment Analysis based on Fast Fourier Transform over Temporal Intuitionistic Fuzzy Value

Basanti Pal Nandi (✉ basanti_pal@yahoo.com)

  Guru Tegh Bahadur Institute of Technology   https://orcid.org/0000-0002-3889-5669

Amita Jain

  Ambedkar Institute of Advanced Communication Technologies and Research

Devendra Kumar Tayal

  Indira Gandhi Delhi Technical University for Women

Poonam Ahuja Narang

  Guru Tegh Bahadur Institute of Technology

Research Article

High Performing Sentiment Analysis based on Fast Fourier Transform over Temporal Intuitionistic Fuzzy Value

Basanti Pal Nandi[a,*],Amita Jain[b],Devendra Kumar Tayal[c],Poonam Ahuja Narang[d]

[a]Guru Tegh Bahadur Institute of Technology,New Delhi,India e-mail-basanti_pal@yahoo.com +918447765628

[b]NSUT, Delhi , India

[c]Indira Gandhi Delhi Technical University for Women, Delhi,India

[d]Guru Tegh Bahadur Institute of Technology,New Delhi,India

Abstract

Sentiment analysis or opinion mining has an extensive area in the field of research. Today we consider the huge amount of structured and unstructured data available in the web for a particular subject to get an opinion. The surplus data handling termed as big data requires some new technology to deal with. This paper considers the requirement of sentiment analysis of such huge data for fast processing. Based on Fast Fourier Transform on Temporal Intuitionistic fuzzy set generated from text, this algorithm (FFT-TIFS) expedites the sentiment classification. Fourier analysis converts a signal from its time domain to its representation in frequency domain. Such frequency domain algorithm on Temporal Intuitionistic fuzzy set is used in Sentiment analysis for the first time. This algorithm is useful for short twitter text, document level as well as sentence level binary sentiment classification. It is tested on aclImdb, Polarity, MR, Sentiment140 and CR dataset which gives an average of 80% accuracy. The proposed method shows significant improvement in required time complexity where the method achieves 17 times faster processing in comparison to sequential Fuzzy C Means(FCM) method and again it is at least 7 times faster than distributed FCM method present in literature. The method presented in this paper has a novel approach towards fastest processing time and suitability of various sizes of the text sentiment analysis.

KeyWords: Temporal Data; Intuitionistic Fuzzy; Fast Fourier Transform; Sentiment Analysis; Opinion Mining; SentWordNet

1. Introduction

The need for opinion on a subject or product or on any particular object has a growing importance in the arena of the age of information. Sentiment analysis is the key to get a fast response to have an opinion based on the comments of user and it is considered as a blooming area of research. Sentiment analysis can be categorised with various perspective: Task Oriented, Granularity Oriented and Methodology Oriented. Sentiment classification task mostly classifies the polarity with positive, negative or neutral as a binary or ternary classifier. Even classification can distinguish a specific text as an objective sentence or subjective

sentence. Objective sentences refer to facts, happenings and neutral opinions whereas subjective sentences refer to positive or negative polarity values with opinion or belief or judgement. Another sub category of sentiment analysis is Granularity Oriented where opinion is generated on small or large document level, sentence level or word level basis. Researchers are exploring the analysis on large sized documents as well as on big data where counts of data are huge. Classification oriented analysis gives binary classification, ternary classification or multi-level classification. Methodology oriented analysis include Supervised, Semi-supervised and Unsupervised methods. Supervised methods include Rule based, SVM, Regression, Neural Network, Deep Learning etc. Though some of the supervised methods give high accuracy but computational cost is of concern moreover over-fitting needs to be checked and requires a large amount of time for training purpose. Semi-supervised methods are Graph-based method, Wrapper-based method and Topic-based method. Unsupervised methods handle large datasets with fast, simple and effective way.

In recent research Sentiment analysis has been explored through different directions. The most tested area is machine learning. Evolutionary algorithms also have taken part in opinion mining. The combination of machine learning and nature inspired algorithm is blooming area of research now-a-days. Besides algorithm the volume of data is also a major concern in the area of sentiment classification. Recent research shows that big data sentiment extraction uses hadoop distributed file system with map reduce techniques and researchers experimented on big data distributed techniques with machine learning algorithms. These all experiments have a single aim which is to attain less time complexity so that large volume data can be processed efficiently. Keeping in view of this particular large volume data the method proposed in this paper using Fast Fourier Transform on Temporal Intuitionistic fuzzy set gives a suitable method having a competitive time complexity with state-of-the-art techniques even with sequential processing. Moreover, the efficiency of proposed method is also greater than some state-of-the-art algorithms.

In this paper Sentiment of a word represented as Temporal Intuitionistic Fuzzy set. Intuitionistic fuzzy set developed by Atanassov is a powerful extension of classical fuzzy set. It differs from classical fuzzy which assigns only a membership degree to each element. In Intuitionstic fuzzy each element has a membership degree and a non-membership degree as well. Here positive and negative sentiment values of a word generated from SentiWordNet can be represented as membership degree and non membership degree of each word in the context of positivity and negativity. Temporal Intuitionistic fuzzy is a variant of IFS developed by Atanassov where time-moments are also taken into consideration. In this paper positive and negative values of the words are represented as Temopral Intuitionistic Fuzzy set. This time domain fuzzy values are then fed into frequency domain analysis.

The proposed method is based on Fast Fourier Transform of signal processing. Fast Fourier Transform is an algorithm which computes Discrete Fourier Transform of a sequence. FFT has a very wide range of applicability in digital methods such as image compression and encryption, spectral analysis, fourier spectroscopy, signal processing, speech processing or solution of differential equation. The use of FFT is prominent in image analysis such as fingerprint classification or microstructure evaluation etc. But fourier transform algorithms are

not used in text processing. This is a novel method where Fast Fourier Transform is used for sentiment analysis. The Motivation of the use of this algorithm is fast processing in the age of big data and as well as no pre-processing for feature selection of the text is required. Moreover the algorithm does not need any training to generate bi-polar opinion i,e, positive or negative. In addition, with this facility the algorithm gives high efficiency both in document level and sentence level opinion mining. This is an unsupervised method, so training phase is completely eliminated. The proposed method will give a very fast processing in future fast technology or in distributed systems.

1.1 Motivation:

The motivation of the paper is five-fold:

1. In the literature the discrete cosine transform has never been explored in sentiment analysis field. So, the proposed method is novel in this case.
2. While processing big data, the time requirement is a critical issue. This issue is addressed successfully in this research work. This method expedites fastest time complexity in comparison to previous work.
3. While looking into the previous work this has been found that most of the cases a large training data is required to train the system. This requirement is sometimes not available for a new field of study on sentiment analysis. In the FFT-TIFS method this requirement is completely eliminated.
4. In previous methods feature selection is a mandatory step in most of the cases. For large documents or for cross domain or big data unstructured text, feature selection is difficult and confusing. In this method there is no requirement of feature selection.
5. In most of the previous work the suitability of the method is tested on a particular size of dataset. In this paper a variety of type of text- short twitter text, single sentence, 1kb file or 3 kb file, are explored and found suitability for all of them.

1.2 The main contributions of the proposed work are as follows:

1. The proposed method experiencing fastest processing time in computing sentiments in comparison to state-of-the-art methods. It achieves 17 times and 7 times faster processing than sequential Fuzzy C means and distributed FCM method present in the previous work respectively.
2. The method has been tested on short twitter text, on single sentence, medium sized (around 1kb) files, large sized (around 3 kb) files. In all of the cases the proposed process has shown efficient speed and accuracy. So, it can be concluded that the method is suitable for any size of the document level as well as sentence level sentiment analysis.
3. No training phase or feature selection is required in this method, So the availability of large training set is not at all a constraint in the proposed work. This work is suitably applicable for new field of study in sentiment analysis.
4. Fast Fourier Transform is applied here for the first time for sentiment analysis.

The paper is organized as follows: Section 2 describes related work in the field of Sentiment analysis, Fast Fourier Transform and Intuitionistic Fuzzy set. Section 3 describes the technical details of Temporal Intuitionistic fuzzy, Fast Fourier transform, SentiWordNet. Section 4 describes proposed method. Section 5 gives the application of the algorithm on various datasets and their Results and Section 6 draws Conclusion from results and outlines the Future Scope.

2. Related Work

Researchers are trying to analyse opinion mining in various angles of problem statement. The basic property of sentiment analysis is to get polarity of the document or sentences. Decade's research developed the category of the problem into different sections. One category is the level of the problem whether it is sentence level, document level or aspect level. The other is the algorithm used for sentiment analysis i.e, machine learning, fuzzy, evolutionary algorithms. Most recent concern of the problem is the size of the data in viewing Big Data age. In this section some overview of the recent research will be presented.

Sentiment analysis in document level shows whether the sentences appeared in document give polarity of positive or negative value. Tripathy et. al.,2017[38] shows document level binary classification with a high accuracy 96.4% using machine learning techniques. They have compared their hybrid method of SVM and ANN with other algorithms and showed that they reached a greater efficiency. Yessenalina et. al., 2010[44] proposed a two-level document analysis for sentiment which extracts meaningful sentences for correct and accurate classification. They also have reached more than 90% accuracy using variant of SVM algorithm. Research direction on sentence level analysis is finer grained as they have two aspects: finding the sentence as subjective sentence or objective sentence. In case of subjective sentence finding the polarity of the sentence as positive, negative or neutral will complete the task. Dragoni et. al., 2015[14] have worked on Sentence level opinion mining on Blitzer dataset. They have acquired a comparable efficiency with polarity aggregation using Simulated Annealing. Ruz et. al.,2020[33] estimated sentiment analysis on twitter data on a different section of problems. They have used Bayesian networks classifier in critical issues and social movement sentiment analysis. Chilean earthquake and Catalan independence referendum twitter texts are the two datasets on which the Bayesian networks classifiers are evaluated. Another important aspect of texts that are mostly considered for experiment is basically clean data. In the twitter text it has been found that texts are short, informal, ambiguous and polysemi. Naseem et. al.,2020[29] worked on such texts using word representation by transformer based encoding fused with deep intelligence contextual embedding. Jain et. al.,2019[20] worked on larged sized (25Kb) document to perform ternary sentiment classification using evolutionary optimization. Evolutionary optimizations[11,7,12,13,16,52] which are developing fast can be a potential source for the sentiment analysis.

As the proposed method is based on the idea of Fuzzy values some of the application of fuzzy theory on sentiment analysis are discussed here. Krishna et. al.,2018[25] has applied fuzzy set concepts in opinion mining of text reviews posted in the social media sites. In the stage of feature extraction opinion holding words are extracted and assigned a degree of polarity with the help of fuzzy sets. Jefferson et. al.,2017[21] applied Tsukamoto fuzzy rule based approach

for sentiment classification. They have argued that fuzzy system is suitable to hold the linguistic uncertainty. Vashishtha and Susan,2019[39] worked on twitter comments and developed nine fuzzy rules to compute sentiment of each tweet. They proposed unsupervised approach which is suitable for any dataset or any sentiment lexicon. Three different sentiment lexicons are used namely SentiWordNet, AFINN, VADER in isolation and compute the time and efficiency on nine publicly available twitter datasets. Vashishtha and Susan,2021[40] deployed fuzzy linguistic hedges concept on sentiment analysis, as well as they have also shown fuzzy entropy filter and k-means clustering on document level sentiment datasets.

2.1 Machine Learning Approaches:

There are different directions to capture the research trends in Sentiment Analysis problem. One of such path is application of machine learning algorithms in this area. Applications of these algorithms are broadly classified as Supervised, Semi-Supervised and Unsupervised algorithms. In literature survey we got that Ensemble, Regression, Hidden Markov Model, Gaussian Mixture Model are used in Sentiment classification. Recent trends for machine learning are implementation of Neural Networks and its broader family Deep Learning. Sharma and Dey,2013[36] developed an approach for Back Propagation Artificial Neural Network with Sentiment Lexicon to reach accurate result by reducing dimensionality. Zhang et. al.,2016[47] showed a way to use bi-directional gated neural network for sentiment classification. They have developed a way to use pooling function in hidden layers for connecting the words of the text. The extension of Neural Network is Deep Learning Techniques which are successfully applied over Natural Language Processing Models including sentiment analysis. Deep Learning networks are useful for selecting complex features of text for processing having less human intervention. Araque et. al.,2017[2] proposes a deep learning classifier using machine learning algorithm and word embedding model. The deep learning approaches which are used in sentiment analysis are CNN, Recursive NN, Recurrent NN(LSTM,GRU), Deep Belief Network, Attention based network, Bidirectional RNA and Capsule Network. Wang et. al., 2016[41] proposed attention based long short term memory (LSTM) approach on SemEval 2014 dataset which gave a state-of-the-art performance. In sequence Tang et. al.,2016[37] introduced a deep memory network for aspect based sentiment analysis which gives better result than LSTM or attention based LSTM. Combining the different deep learning methods is a recent blooming trend. Combining CNN and RNN is an important convergence to capture long term dependencies and which is applied in sentence classification. Hassan and Mahmood,2017[17] combined CNN and LSTM to get sentiment on IMDB and SSTb dataset and acquired efficient result. Yang et. al.,2018[43] proposed an attention network for target dependent sentiment classification. They have experimented on twitter of both English and Chinees datasets. In this study a target dependent sentiment classification is proposed and features are selected on the basis of unigram content feature, word position feature and POS feature. Behera et. al.,2021[6] also use deep learning combined model of CNN and LSTM for an improved method of examining big social data sentiment analysis. They have used CNN for automatic extraction of features of big social data and shown

that their model has the capability of domain independence solution provider. To prove the point of domain independence they have tested it on variety of datasets.

The use of deep learning networks is quite successful in this era of big data. A combination of Map-Reduce technique with Machine Learning algorithms, Fuzzy methodologies are also explored on Big Data. Liu et. al.,2017[26,27] applied Naive Bayes algorithm on big data and showed 82% accuracy on 2000k data over hadoop implementation. Phu et. al.,2017[32] applied a fuzzy C Means method on Hadoop Map/Reduce for sentiment classification of English sentences. They have shown 60.2% accuracy in a very competitive time.

2.2 Intuitionistic Fuzzy Applications:

IFS and its variants have been applied on various fields like electoral system, medical pattern recognition, petrochemical farm, medical diagnosis, sociometry, pneumatic transportation process etc. To name some of the examples fuzzy methods have been successfully applied in image segmentation. Huang et. al.2015[18] applied Intuitionistic fuzzy to segment MRI images using C-means clustering techniques. In the network system also IFS has been applied by Dutta and Sait,2012[15] for routing. Wang et. al.,2018[42] detected anomaly in network traffic from flow interaction using IFS. Advancement of multi criteria decision making problem has evidence of the use of Intuitionistic Fuzzy values. Zhang et. al.,2020[49] has shown in his research that in multicriteria decision making problem where there are n alternatives and m criteria, how intuitionistic fuzzy values are used while employing fuzzy rough set model. But in literature the use of temporal Intuitionistic fuzzy set is very limited or it can be inferred that it is not used at all. Here the sentiment architecture can be seen as a Temporal IFS. Over this system FFT is applied to get the sentiment value.

2.3 Fast Fourier Transform Applications:

The use of Fast Fourier Transform is a novel approach in Sentiment Analysis. Earlier this fast algorithm is used in many engineering and science domain. It was included in top 10 algorithms of 20th Century by IEEE. To mention some of the recent development Zhang et. al.,2018[48] used Fractional Fourier Transform in color image encryption. They have used 2D compressive sensing to encrypt and compress and then re-encrypt with Fractional Fourier Transform.. Parchami et. al.,2016[33] investigated Short-time Fourier Transform(SIFT) method in speech processing. They concluded that this Fourier family of algorithms are suitable for handling different frequencies independently and can give flexibility to noise statistics to handle speech processing. Dara and Panduga,2015[9] have used 2D FFT along with SVM in Telegu Character Recognition. They have reached 71% accuracy by exploiting 2D FFT. In recent advancement Jeong and Shin,2018[22] uses Fast Fourier Transform to search accurate data from different kind of big data in P2P cloud computing environment.

3. Preliminary

3.1 Intuitionistic Fuzzy Set

Fuzzy set proposed by Zadeh,1965[45] states that belongingness of an element in a set is a matter of degree unlike classical set where membership is a matter of affirmation or denial. Intuitionistic fuzzy set (IFS) is the generalization of fuzzy set, proposed by Atanassov, in 1986[2]. It assigns two values called membership degree and a non-membership degree respectively.

An Intuitionist Fuzzy set A in the domain E is defined according to the following form

$A = \{< x, \mu_a(x), v_a(x) > | x \epsilon E\}$, where $(\mu_a(x))$ is the degree of membership and $(v_a(x))$ is the degree of non-membership which lies in the range [0,1] and $0 \leq \mu_a(x) + v_a(x) \leq 1$. In this paper the positive sentiment is represented by $\mu_a(x)$ and the negative sentiment is represented by $v_a(x)$.

This logic differs from classical fuzzy when the term indeterministic or hesitancy comes and defined in Intuitionistic fuzzy as $\pi_a = 1 - \mu_a(x) - v_a(x)$, It is degree of hesitancy of x to A. When the term π_a becomes 0 the set becomes classical fuzzy set. The alignment of the sentiment values towards Intuitionistic fuzzy is more prominent as there lays a hesitancy or indeterministic part due to $\pi_a = 1 - \mu_a(x) - v_a(x)$ is not equal to zero.

There are few variants of Intuitionistic Fuzzy Sets(Jain et. al.,2020[19]):

a) Interval valued Intuitionistic fuzzy set: This is a combination of Intuitionistic fuzzy and interval valued fuzzy.
b) Intuitionistic L-fuzzy set: Here L may be complete chain, lattice or complete ordered semi-ring.
c) Temporal Intuitionistic Fuzzy set: Here Time element is added with Intuitionistic fuzzy sets.
d) Intuitionistic fuzzy set of second type: Here varied degree of membership and non-membership is counted.

In this paper rather than defining the sentiment value as IFS , it is preferred to represent it as temporal IFS due to the time domain requirement.
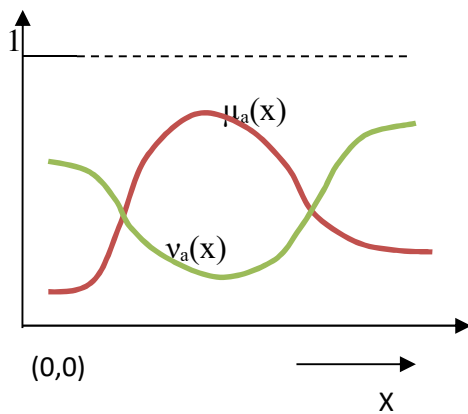

Fig1 : Geometrical Representation of Intuitionistic Fuzzy set where $\mu_a(x)$ is the membership value and $v_a(x)$ is the non-membership value. $\pi_a = 1 - \mu_a(x) - v_a(x)$

3.1.1 Temporal Intuitionistic Fuzzy Set

Time is an important factor in real world system. An object can be defined with an instance of time. Time is required to record when an object is changing its parameters. An instance of Temporal Intuitionistic Fuzzy Set A(T) is defined over non empty set E and T where elements of T is called 'Time-moment'.

$A(T) = \{< x, \mu_a(x,t), v_a(x,t) > | (x,t)\epsilon \text{ E x T}\}$,

where:

a) $A \subset E$ is a fixed set,
b) $\mu_a(x,t) + v_a(x,t) \leq 1$ for every (x,t)ϵ E x T
c) $\mu_a(x,t)$ and $v_a(x,t)$ are the degree of membership and non-membership value of the element x ϵ E at the time t ϵ T

Every ordinary IFS can be represented by Temporal IFS where T is a singleton set. Here also the sentiment values are simple IFS where it is converted to Temporal representation for T as a singleton set.

3.2 Fast Fourier Transform

A Fast Fourier Transform algorithm is a Discrete Fourier Transform(DFT) of a sequence. Fourier Analysis converts a sequence of time or space domain to a sequence of frequency domain. A DFT is obtained decomposing a sequence of values into component of different frequencies. DFT is same as Continuous Fourier Transform for signals known only at N instances separated by sample times T. Since, there are only finite numbers of data point; DFT treats the data as if it were periodic.

Let f(t) be the continuous signal, which is the source of the data. Let N samples be denoted by f[0],f[1],f[2],.......,f[k],....,f[N-1]. The Fourier transform of original signal f(t) will be

$$F(jw) = \int_{-\infty}^{+\infty} f(t)e^{-jwt}dt \qquad -------(i)$$

Since, integrand exists at the sample points

$$F(jw) = \sum_{k=0}^{N-1} f(k)e^{-jwt} \qquad -------(ii)$$

F(n) is the discrete fourier transform of f(k).

The disadvantage of DFT is that it is an approximation since it provides only a finite set of frequencies. There are two types of errors in DFT namely aliasing and leakage. If the initial samples are not sufficiently closely spaced to represent high frequency components present in the underlying function then the DFT values will be corrupted by aliasing. The solution is to increase the sampling rate. Continuous Fourier Transform of a periodic waveform requires the integration to be performed over an integer number of cycles of the waveform. If a non-integer cycle of input signal is to be under consideration then the transform may be corrupted.

The time taken to compute DFT is mainly dependent on number of multiplication involve in the process as multiplication is the slowest operation. With the DFT, this number is directly related to N^2 for the signal of length N. Highly efficient computer algorithms to compute DFT known as Fast Fourier Transform(FFT) are developed in early 60's on the basis that standard DFT calculation involves lot of redundant calculation. The DFT requires N^2 complex multiplications. At each stage of the FFT N/2 complex multiplications are needed to combine the results of the previous stage. Since there are $\log_2 N$ stages the number of complex multiplication requires $(N/2)*\log_2 N$. Such reduction in time complexity made FFT very useful and popular in many fields of study where DFT had used. FFT converts discrete data into continuous datatype at various frequencies. While FFT requires less processing power but for the real world problem it is difficult to achieve same accuracy as that of DFT. FFT mathematically works on divide and conquer method where an integer window is required. But for the real world problem it is difficult to obtain 2^n window to provide same accuracy as that of DFT. The resultant inaccuracy is called "Harmonic Leakage".

3.3 SentiWordNet

In the proposed method SentiWordNet 3.0 is used for the polarity of words present in the text. It is an improved version of SentiWordNet 1.0 which is publicly available for research purposes. SentiWordNet derives an automatic annotation of the synsets of words present in WordNet with the values of positive, negative and neutrality. Each of these scores ranges in the interval [0.0,1.0] and their sum is 1.0 for each synset. The synset may have non-zero scores for all the three opinion related properties. Weak supervision or semi supervised algorithm are used for SentiWordNet1.0 whereas for SentiWordNet3.0 semi-supervised algorithm is used for intermediate stage of annotation process and the result is fed to an iterative random walk process that is run to convergence. After convergence has reached it gives the output for SentiWordNet3.0. Denecke,2008[10] used this SentiWordNet for getting document polarity of German Movie Review in Amazon. Ohana and Tierney,2009[30] also used this lexical resource for getting film review opinion.

4. Proposed Method

The text of large document or the sentence set for the classification purpose is parsed and gone through POS tagging. Noun, Verb, Adjective and Adverbs are taken for the sentiment value generation. The positive and negative values of the words are analogous to IFS membership ($\mu_a(x)$) and non-membership ($\nu_a(x)$) components. This representation is valid as $0 \leq \mu_a(x) + \nu_a(x) \leq 1$. The proposed method converts the membership and non-membership values as time domain representation. In this format, as the length of the text increases the time increases. The length of the text is the time axis in this case. So the positive negative values can again be specialized with Temporal IFS where positive is the degree of membership is a time domain value $\mu_a(x,t)$ and negative is non-membership time domain value $\nu_a(x,t)$.
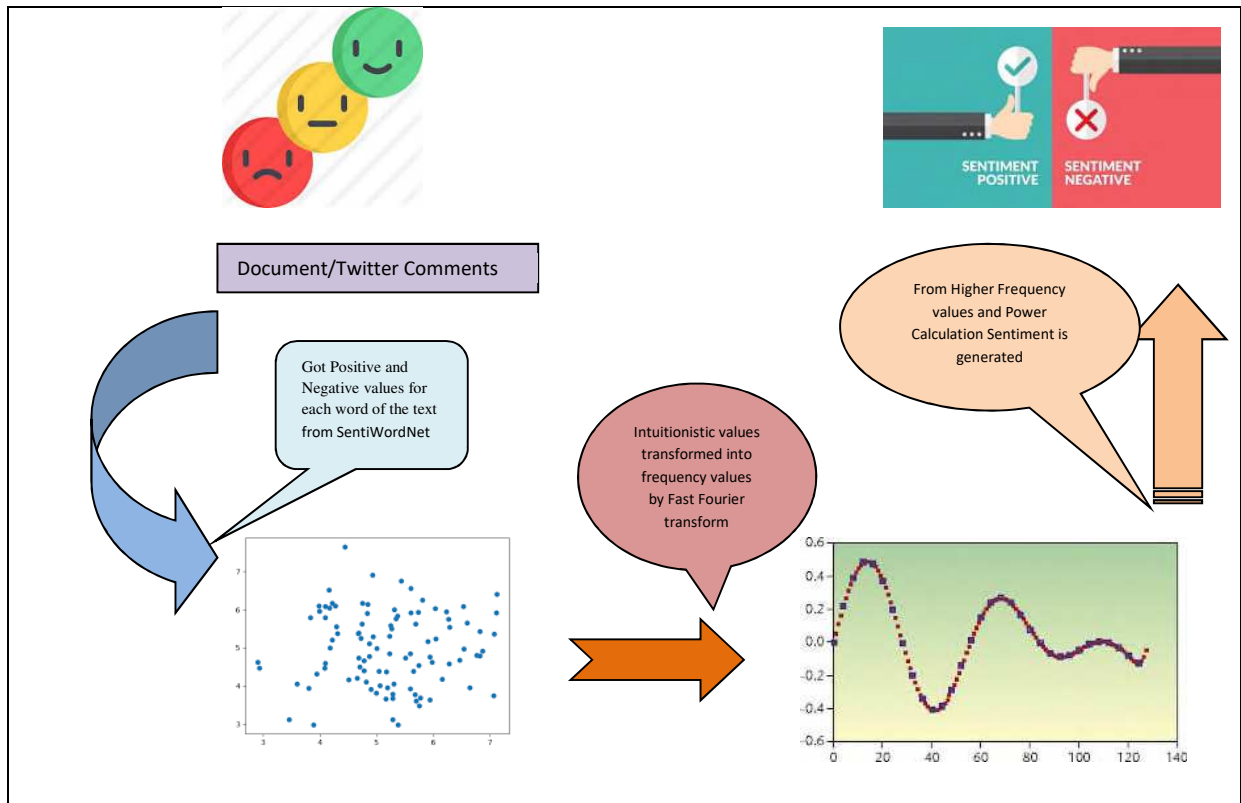
Fig 2: Concept diagram for FFT-TIFS binary sentiment analysis

This representation is novel as Temporal IFS application has never been done in the literature. Temporal IFS time domain values are then fed to Fast Fourier Transform. The time domain values are then transferred into frequency domain value. Fast Fourier Transform gives complex values after transformation. However, in this process only real values are used for classification purpose. The amplitude of angular frequency at an angle $\pi/2$ are taken into consideration for sentiment classification purpose. The absolute values of the real part of membership as well as non-membership fuzzy values after FFT transformation are then used to calculate Power term. FFT values of membership and non-membership fuzzy real part and the sum of the calculated power values are then used for classification purpose.

4.1 Algorithm:

1. Input Positive or Negative sentence or text of a document
2. Parsing and POS tagging
3. Noun, Verb, Adjective and Adverb words are taken
4. Positive and Negative score from Sentiwordnet 3.0 for each taken words are extracted
5. Positive and Negative values are represented a Temporal Intuitionistic Fuzzy set

Positive=membership degree of TIFS ($\mu_a(x, t)$) and Negative=non-membership degree of TIFS($v_a(x, t)$) where x is the words and t is the position of the word in the text which represented as time

6. These Temporal values are represented as time domain signal where length of the text is the time axis.

7. The membership degree $\mu_a(x, t)$ and non-membership degree $v_a(x, t)$ values for words of each document/sentence are fed to Fast Fourier Transform where x is the word of the text at t position.

8. Let FT(n)=Fast Fourier Transform of Membership or Positive value $\mu_a(x, t)$ And FF(n)=Fast Fourier Transform of Non-Membership or Negative value $v_a(x, t)$ where n is the angular phase and FT and FF are the amplitudes at that angle.

9. $\text{Power\_FT(n)} = \dfrac{\Sigma absolute(FT(n))^2}{\Sigma x}$ $\text{Power\_FF(n)} = \dfrac{\Sigma absolute(FF(n))^2}{\Sigma x}$

10. $Sum_{Power_{YT}} = \Sigma Power\_YT(n)$ $Sum_{power_{YF}} = \Sigma Power\_YF(n)$

11. Let FT(2) = Amplitude of angular frequency at an angle $\pi/2$ of transformed FFT series from time domain series $\mu_a(x, t)$ and FF(2) = Amplitude of angular frequency at an angle $\pi/2$ of transformed FFT series from time domain series $v_a(x, t)$.

12. IF((FT(2)>FF(2)) $\parallel$ $Sum_{Power_{YT}} > Sum_{power_{YF}}$)

    a. Document/Sentence has Positive Polarity

    Else

    a. Document/Sentence has Negative Polarity

_____

Fig 3: Algorithm for FFT-TIFS sentiment analysis

4.2 Explanation of the algorithm:

The algorithm of the FFT-TIFS has been given in Fig3. Here the process of the algorithm and the types of values which the method came across are explained with examples.

i. The dataset files are undergone parsing and POS tagging

ii. The words in the files or sentences are converted into sentiment score from SentiWordNet.

iii. As an example: "Opening" word has SentiWordnet value Positive:0.375 and Negative:0.0

iv. The whole text's or the sentence's noun, verb, adjective or adverb are taken and converted into Sentiwordnet values which are now represented as Temporal Intuitionistic value as the position of the word in the text is represented as time.

v. These membership degree of TIFS and non-membership degree of TIFS now fed into Fast Fourier Transform.

vi. Fast Fourier Transform gives series of values as an example 0.8627-9.4087i ,0.2210-4.6019i and so on.

vii. For calculation of Power term for Membership and non-Membership values only real and absolute part of FFT values will be taken.

viii. Example of such values are 0.0457,0.0218 etc.

ix. Summation of Power Terms for Membership or non-Membership values are calculated

x. Example of Sumpower Membership = 35.3909 Sumpower nonMembership = 33.6972

xi. Example of Amplitude of angular frequency at an angle $\pi/2$ of Membership FFT is 2.7197

xii. The values of Amplitude of angular frequency at an angle $\pi/2$ and Summation of Power terms of Membership and Non-Membership FFT values are then used to calculate Sentiment.

The method used in this paper requires eclipse and matlab for the processing. Java programming done in eclipse made available the SentiWordNet values for positive and negative polarity. Matlab is used for further processing of FFT and draws conclusion about the document/sentence overall polarity. Here initial values of positive and negative polarity considered as a time domain signal over Temporal Intuitionistic values which is then changed to frequency domain discrete fourier transform through Fast Fourier Transform algorithm. Then high frequency values are taken to consider the polarity of the documents/sentences.
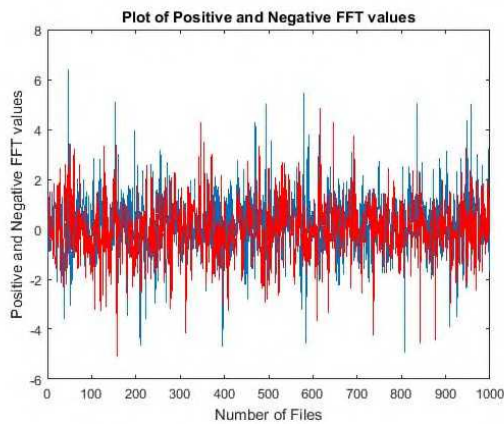

Fig 4: Plot of Positive and Negative FFT values at π/2 angle of 1000 positive aclImdb files
—— Positive values
—— Negative values

Fig 5: Plot of Positive and Negative Power values of 1000 positive aclImdb files
—— Positive values
—— Negative values

This figure is a plot of positive negative values of a positive file from aclImdb dataset. The blue values are the FFT conversion values of positive or membership values of Temporal IFS. The Red values are the FFT conversion values of negative or non-membership values of Temporal IFS. This figure shows that the tendency of blue waves is higher in positive sides and so classified the document as positive document.

The figure below shows sum of power spectrum values of membership(Positive) and non-membership(Negative) FFT values of time domain Temporal IFS values of a positive file from

aclImdb dataset. Power spectrum values are calculated as square of absolute values of derived FFT terms. The Blue color represents power spectrum values of derived FFT values of time domain membership signals while Red color represents power spectrum values of derives FFT values of time domain non-membership signals. 1000 positive files taken for the particular graph. It can be inferred from the graph is that for positive files the blue wave have the higher spectrum values.

For the negative files the graph shown below inferred that the Red values for non-membership temporal signals have higher magnitude after transforming to Fast Fourier transformation. Same is the case for power spectrum values in which the magnitude of Red values are greater than Blue waves which are membership temporal signals after discrete fourier transformation.

Fig 6: Plot of Positive and Negative FFT values at π/2 angle of 1000 negative aclImdb files
— Positive values
— Negative values

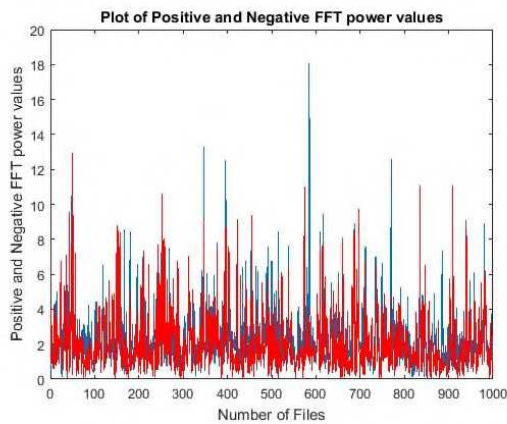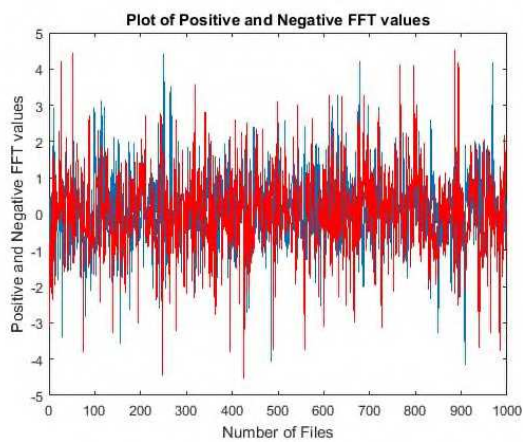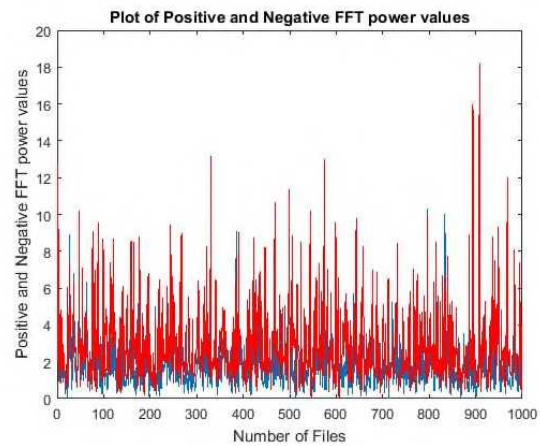
Fig 7: Plot of Positive and Negative Power values of 1000 negative aclImdb files
— Positive values
— Negative values

The fuzzy values of positive and negative sentiment which turn as membership and non-membership values in Temporal intuitionistic fuzzy logic used as a time domain parameter to calculate sentiment of the document. The time here represented by the number of words sequentially calculated in the text document. This time series is then transformed into frequency domain through Fast Fourier Transform. The combination of higher frequency amplitude of the real part of Fast Fourier Transform and the calculated power term is then used for analysis. The algorithm is simple, fast and easy to implement. Besides the benefit of fast implementation the algorithm works competitively with a wide range of document size.

4.3 Computational Complexity of the Presented Method

As it has discussed in the previous section that FFT gives better time complexity in comparison with DFT. The FFT requires $N\log_2 N$ operations while DFT requires N^2. In view of proposed algorithm the pre-processing step for tokenization and POS tagging (In step 5 in Fig 3) requires $O(N)$ operations to get sentiwordnet score while N is the number of words in a sentence for

sentence level analysis or in a text for document level analysis. To get FFT(In step 8 in fig3) of these N temporal values the complexity is $O(Nlog_2N)$. To get power calculation (step 9 and 10 in Fig 3) requires $O(1)$ step. Rest of the comparison (step 12 in Fig 3) requires $O(1)$ time complexity. So, it can be concluded that the time requirement of the algorithm is $O(Nlog_2N)$ as that of FFT.

5. Experimental Analysis and Results

In this section a detailed experimental analysis is presented and compared the method with state-of-the-art methods presented in the literature. Here emphasis is given on the Big data processing. In current scenario big data has a huge importance due to lots of usage of digital media which leads to ample number of document storage. For processing of such volume of data a fast algorithm is required. Moreover, the unstructured characteristic of big data requires an algorithm which will act uniformly over all variety. Here lies the strength of this algorithm which acts on the big data property such as volume, velocity and variety. The time required for processing of text whether it is single sentence or large document is in milliseconds retaining 80% accuracy. Thus, the claim that this method is suitable for big data is quite justified.

The proposed method is tested on documents as well as on sentences. Two document level datasets are taken which are aclImdb and Polarity dataset. AclImdb is a movie review dataset having 1Kb size and Polarity dataset have texts of around 3Kb size. Twitter and Sentence level datasets are taken as well such as Sentiment140, MR Rt-Polarity and CR datasets. It is noticed that the method is suitable for both document and sentence level sentiment classification. The results are shown as comparison to other results of previous research on sentiment analysis. The results are shown in terms of Precision, Recall, F-Measure and Accuracy.

$$Precision = \frac{TP}{TP+FP} \qquad --------(iii)$$

$$Recall = \frac{TP}{TP+FN} \qquad --------(iv)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad --------(v)$$

$$F-Measure = 2.\frac{Precision.Recall}{Precision+Recall} \qquad --------(vi)$$

5.1 AclImdb dataset*

AclImdb is a document level dataset having text of 1Kb size (Avg. 100 words per file). IMDB dataset has 25000 highly polar positive and negative reviews. In which 9999 files are tested for each category of positive and negative sentiment. Overall efficiency came 86.25% where

Polarity Dataset http://www.cs.cornell.edu/people/pabo/movie-review-data/

Sentiment 140 Dataset https://www.kaggle.com/kazanova/sentiment140

Rt-PolarityDataset http://www.cs.cornell.edu/People/pabo/movie-review-data/rt-polaritydata.tar.gz

CR Dataset https://github.com/AcademiaSinicaNLPLab/sentiment_dataset

aclImdb Dataset https://ai.stanford.edu/~amaas/data/sentiment/

average time taken for classification of each file is 0.214 second. The results of applying proposed method is compared(Table 2) with machine learning and deep learning methods present in literature (Behera et. al.,2021[6]) and it is derived that FFT-TIFS can give maximum

F-Measure and accuracy with comparison to the mentioned machine learning and deep learning methods.

Table 1: Classified Positive Negative files on aclImdb dataset

	Positive	Negative
Positive(9999)	8279	1720
Negative(9999)	1029	8969

Table 2: Measures of aclImdb dataset with comparison of other methods

Method	Precision	Recall	F-Measure	Overall Accuracy(%)
SVM	.832	.826	.829	83.1
NB	.898	.723	.801	78
Linear Regression	.805	.801	.803	80.5
Random Forest	.764	.602	.674	63.5
CNN	.80	.829	.814	82
RNN	.749	.781	.764	77.2
Co-LSTM	.835	.835	.83	83.1
Proposed Method	.889	.828	**.857**	**86.3**

5.2 Polarity dataset

Polarity dataset is a movie review dataset and its label was created with an improved rating-extraction system. It contains 1000 positive and 1000 negative files having an average of 3-5Kb size(Avg. 350 words per file). Overall efficiency came 84.89% where average time taken for processing of each file is .356 seconds. A comparison chart is given for the Fuzzy processes present(Table 4) in the literature which shows significant improvement in overall efficiency.

Table 3: Classified Positive Negative files in Polarity dataset

	Positive	Negative
Positive(1000)	781	219
Negative(1000)	83	916

Table 4: Measures of Polarity dataset and comparison with Fuzzy Methods

Methods	Precision	Recall	F-Measure	Overall Efficiency(%)
Linguistic Hedges in Fuzzy sentiment[40]	-	-	.65	65
Fuzzy Phrase level SA[40]	-	-	.701	70
Proposed Method	.904	.781	.838	84.89

5.3 Sentiment 140 dataset

Sentiment 140 is a twitter dataset having 1600000 tweets extracted by twitter api. This dataset is created by Standford University. Here 15856 tweets are taken for positive and 15065 taken for negative sentiment processing. As tweets are short text having 7 words per sentence, the processing for such texts took less time than document processing. For each tweet the algorithm takes an average of .033 seconds. Overall efficiency came 79.6%. Precision and Recall values are compared (Table 6) with fuzzy approach (Vashihstha and Susan,2019[39]) and with some deep learning methods(Table 7) [Basiri et. al.,2021[5]]. It can be derived from the comparison that the proposed method has comparable precision, recall and accuracy with the deep learning approaches too. Deep learning approaches require exhaustive training phase whereas FFT-TIFS does not require it at all. The achieved higher Precision and recall are shown in bold.

Table 5: Classified Positive Negative sentences on Sentiment 140 dataset

	Positive	Negative
Positive(15856)	12890	2966
Negative(15065)	3347	11718

Table 6: Measures of Sentiment 140 dataset and comparison with Fuzzy method

Method	Precision	Recall	F-Measure	Overall Efficiency(%)
Fuzzy-Rules[39]	.628	.661	.644	-
Proposed Method	.794	.813	.803	79.6

Table7:Measures of Sentiment 140 dataset and comparison with Deep-Learning Methods

Method	Class	Precision	Recall	F-Measure	Overall Efficiency(%)
ARC[5]	Pos	.731	.908	.81	78.7
	Neg	.879	.666	.757	
CRNN[5]	Pos	.747	.903	.818	79.8

	Neg	.878	.693	.775	
AC-BiLSTM[5]	Pos	.776	.887	.828	81.5
	Neg	.868	.744	.801	
ABCDM[5]	Pos	.772	.901	.832	81.8
	Neg	.882	.744	.807	
Proposed Method	Pos	**.794**	.813	.803	79.6
	Neg	.778	**.798**	.788	

5.4 Rt-Polarity dataset

Rt-Polarity dataset contains 5331 positive and 5331 negative snippets. All snippets were labelled automatically. As the snippets are short sentences (avg. 17 words per sentence), so the time taken for average file processing is very short i.e,.026 seconds. Here comparison of MR dataset has done with Bag-Of-Words using Machine Learning methods(Table 9) and SAPCP(Song et.al.,2020[35])method where sentiment information are extracted from SentiWordNet and then converted to PLTS and finally classification has done with SVM. Though it is showing greater accuracy than proposed method but presented method is suitable for any sizes of sentences or documents. Whereas SAPCP method is only suitable for shorter texts.

Table 8: Classified Positive Negative snippets of Rt-Polarity dataset

	Positive	Negative
Positive	4266	1065
Negative	1130	4201

Table 9: Measures of Rt-Polarity dataset and comparison with Machine Learning methods

Method	Precision	Recall	F-Measure	Overall Efficiency(%)
BOW+NB[35]	.75	.78	.76	-
BOW+SVM[35]	.75	.76	.75	-
BOW+LR[35]	.76	.77	.76	-
SAPCP[35]	.87	.81	.84	84.2
Proposed Method	.791	.8	.795	79.4

5.5 CR dataset

CR datasets are the customer reviews (avg. 25 words per review) of various products like Camera, MP3 etc. where positive or negative reviews are need to be predicted. These are also short text and have shown 86.6 % efficient classification. Average time taken is .035 seconds for each text to analyze sentiment. The accuracy of the CR dataset has shown better results

(Table 12) with many machine learning methods. Machine learning methods require training phases whereas FFT-TIFS does not require any training at all.

Table 10: Classified Positive Negative reviews from CR dataset

	Positive	Negative
Positive	996	115
Negative	157	757

Table 11: Measures of CR dataset

Precision	Recall	F-Measure	Overall Efficiency(%)
.864	.896	.88	86.6

Table 12: Comparison of the Proposed method with Machine Learning methods

Method	Accuracy
NBSVM[24]	81.8
Tree-CRF[24]	81.4
CNN-rand[24]	79.8
Ensemble-HMM[24]	87
Proposed Model	86.6

Table 13: Comparison table of the proposed method with other existing methods

Author	Method	Dataset	Year	Accuracy
Ju & Yu[23]	CNN	MR-Polarity	2018	.765
Apple et. al.[1]	NB	MR Polarity	2016	.67
Apple et. al.[1]	ME	MR Polarity	2016	.67
Proposed Model	FFT-TIFS	MR-Polarity	2021	.794
Salvetti et al.[34]	NB	aclImdb	2004	.796
Tripathy et. al.[38]	SVM	aclImdb	2005	0.84
Tripathy et. al.[38]	SVM + ANN	aclImdb	2017	.95
Proposed Model	FFT-TIFS	aclImdb	2021	.863
Moraes et.al	NB	Polarity	2013	.803
Tripathy et. al.[38]	SVM	Polarity	2005	.937
Tripathy et. al.[38]	SVM+ANN	Polarity	2017	.964
Proposed Model	FFT-TIFS	Polarity	2021	.849
Coletta et. al.[8]	SVM	Twitter	2014	.793

Nagarajan & Gandhi[28]	SVM+KNN	Twitter	2018	.76
Nagarajan & Gandhi[28]	PSO+GA+DT	Twitter	2018	.90
Proposed Model	FFT-TIFS	Twitter	2021	.796

The above mentioned tables represent that the proposed model have comparable potentiality in comparison to machine learning and deep learning methods. In some cases it gives better result while comparing with machine learning algorithms. Though our focus is on the time complexity that the FFT-TIFS method is generating due to suitability of application on large volume of document or sentences of BigData but this method shows a higher performance on accuracy comparison also. The feature selection method is necessary and mandatory step for the algorithms applied based on machine learning. Feature selection is a time consuming task for large documents and it is unmanageable task for cross domain documents. FFT-TIFS is completely independent from this feature selection task.

Table 14: Comparison of the proposed model with state-of-the-art BigData sentiment analysis methods

Author	Method and Dataset and avg. words per file	Year	Accuracy	Precision	Recall	F-Measure	Average Time per file(in Seconds)
V.N.Phu et. al.[32]	Fuzzy C-Means on English Movie review dataset t1 (100 words per file) using sequential Environment	2017	60.2%	.602	.602	.602	6.02
V.N.Phu et. al.[32]	Fuzzy C-Means on English Movie review dataset t1(100 words per file) using cloudera distributed Environment	2017	60.2%	.602	.602	.602	1.51
V.N.Phu et. al.[32]	Fuzzy C-Means on English Movie review dataset t2(100 words per file) using sequential Environment	2017	59.8%	.592	.589	.59	6.06

V.N.Phu et. al.[32]	Fuzzy C-Means on English Movie review dataset t2(100 words per file) using cloudera distributed Environment	2017	59.8%	.592	.589	.59	1.52
Proposed Model	FFT-TIFS on aclImdb dataset(document level analysis having 100 words per file) using sequential environment	2021	86.3%	.889	.828	.857	.214
Proposed Model	FFT-TIFS on Polarity dataset(document level analysis having files 350 words per file) using sequential environment	2021	84.9%	.904	.781	.838	.356
Proposed Model	FFT-TIFS on Sentiment140 dataset (Sentence level having 7 words per file) using sequential environment	2021	79.6%	.794	.813	.803	.033
Proposed Model	FFT-TIFS on MR Rt-Polarity Dataset(Sentence level sentiment having 17 words per file) using sequential environment	2021	79.4%	.791	.8	.795	.026
Proposed Model	FFT-TIFS on CR dataset(Sentence level sentiment having 25 words per file) using sequential environment	2021	86.6%	.864	.896	.88	.035

V.N.Phu et. al.[32] used Fuzzy C Means for big data as in the present scenario big data analysis is an blooming research field. In this case as the data size is large so processing of sentiment

analysis needs to be faster. As shown by the mentioned paper, the time taken for the classification of positive negative review by cloudera distributed environment is faster than the time taken by the algorithm on sequential environment. It is shown from the table that the proposed method is at least 17 times faster and at most 28 times faster than the state-of-the-art method in sequential environment itself on same dataset. It is therefore assumed than in distributed environment the proposed process will give a greater efficiency suitable for big data processing purpose.

5.6 Comparison of Processing time with the size of dataset

Table 15: Distribution of processing time of the FFT-TIFS algorithm:

| Dataset with avg. words per file	Parsing and POS tagging time on Eclipse(per file in Sec)	Processing time of FFT-TIFS on Matlab(per file in Sec)	Logarithm(base 10) of No. of words per file
Sentiment 140(7 words per sentence)	.027	.005	0.84
MR-Polarity(17 words per sentence)	.017	.008	1.23
CR(25 words per sentence)	.022	.012	1.39
AclIMDB(100 words per file)	.14	.066	2
Polarity(350 words per file)	.258	.098	2.54
25Kb file generated from Blitzer dataset(4500 words)	243.6	.407	3.65
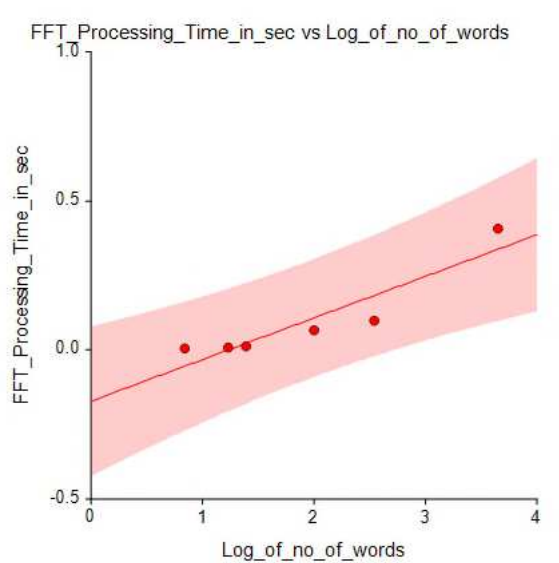
Fig:8 Plot of FFT processing time Vs Logarithm of no. of words per file

The motive of presenting Table 15 is for comparison of time taken for pre-processing in eclipse and for processing of FFT-TIFS algorithm in matlab with the size of the dataset. For comparison purpose one large dataset of each of 25 kb file of positive and negative sentiment is created from Blitzer dataset. The comparison table shown in Table 15 between words taken for a single file or sentence verses SentiWordScore processing time in Eclipse and FFT algorithm processing time in Matlab. It is shown in the figure 8 that the FFT processing time is almost linear to the logarithmic(base 10) of number of words per file.

6. Conclusion and Future Scope

In this paper a method based on Discrete Fourier Transform is proposed for sentiment analysis on Temporal Intuitionistic Fuzzy set consists of membership (Positive) and non-membership(Negative) values. The Fast Fourier Transform is used for fast calculation of DFT. This method is novel as such frequency domain transformation is never used in sentiment classification. The time complexity and accuracy reveals that the proposed method can be very useful for recent trend of big data classification. Document level, sentence level and twitter data all are passed through the system and noticed that the method is suitable for all of the categories. Moreover the pre-processing and feature selection are not required which gives suitability for cross domain and large sized text opinion mining. The accuracy reached 86% on document level and sentence level classification and about 79.6% on twitter classification. Time domain analysis shows that even the sequential implementation of FFT-TIFS is far better than previously applied FCM method on big data over distributed environment. Hence the conclusion can be inferred that in distributed environment the FFT-TIFS will give a more efficient result.

In this paper we have shown corresponding relations of positive and negative values of the text with Temporal Intuitionistic Fuzzy membership and non-membership values. The temporal relation is valid over here as the values are taken in time domain to convert it to frequency domain by Fast Fourier Transform for further analysis. This representation is also novel as Temporal Intuitionistic Fuzzy has never been used in the literature for sentiment classification.

The efficiency of the method looks less in comparison of some hybrid machine learning and deep learning methods whereas for singly used machine learning(NB,SVM) or deep learning method(CNN) the proposed process is much better. An improvement of accuracy can be done with hybridization of machine learning, deep learning or nature inspired algorithms with FFT-TIFS. The scope of the paper can be extended to measure the hybrid algorithm FFT-TIFS with evolutionary or machine learning on big data processing as well. Recent Fuzzy domain development such as multicriteria decision making processes (Zhan et.al,2021[46], Zhan et. al.,2020[49]) can be utilized for multiway sentiment analysis using FFT classification. In the artificial text processing the incomplete information can be tested with fuzzy application on basis of FFT. This method needs more exposure of decision making on unclean incomplete texts as well as other branches of NLP like topic modelling, question answering etc.

Compliance with Ethical Standards:

Conflict of Interest: The authors of the paper declare that we have no conflict of interest.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

References

[1]Appel, O., Chiclana, F., Carter, J., & Fujita, H. (2016). A hybrid approach to the sentiment analysis problem at the sentence level. Knowledge-Based Systems, 108, 110-124.

[2]Araque, O., Corcuera-Platas, I., Sanchez-Rada, J. F., & Iglesias, C. A. (2017). Enhancing deep learning sentiment analysis with ensemble techniques in social applications. Expert Systems with Applications, 77, 236-246.

[3]Atanassov, K. T. (1986). Intuitionistic fuzzy sets. Fuzzy sets and Systems, 20(1), 87-96.

[4]Atanassov, K. T. (2001). Temporal Intuitionistic fuzzy relations. In Flexible Query Answering Systems (pp. 153-160). Physica, Heidelberg.

[5] Basiri, M. E., Nemati, S., Abdar, M., Cambria, E., & Acharya, U. R. (2021). ABCDM: An attention-based bidirectional CNN-RNN deep model for sentiment analysis. Future Generation Computer Systems, 115, 279-294.

[6]Behera, R. K., Jena, M., Rath, S. K., & Misra, S. (2021). Co-LSTM: Convolutional LSTM model for sentiment analysis in social big data. Information Processing & Management, 58(1), 102435.

[7] Cai, X., Zhao, H., Shang, S., Zhou, Y., Deng, W., Chen, H., & Deng, W. (2021). An improved quantum-inspired cooperative co-evolution algorithm with muli-strategy and its application. Expert Systems with Applications, 171, 114629.

[8]Coletta, L. F. S., da Silva, N. F. F., Hruschka, E. R., & Hruschka, E. R. (2014, October). Combining classification and clustering for tweet sentiment analysis. In 2014 Brazilian Conference on Intelligent Systems (pp. 210-215). IEEE.

[9]Dara, R., & Panduga, U. (2015). Telugu Handwritten Isolated Characters Recognition using Two Dimensional Fast Fourier Transform and Support Vector Machine. International Journal of Computer Applications, 116(5).

[10]Denecke, K. (2008, April). Using sentiwordnet for multilingual sentiment analysis. In 2008 IEEE 24th international conference on data engineering workshop (pp. 507-512). IEEE.

[11] Deng, W., Shang, S., Cai, X., Zhao, H., Zhou, Y., Chen, H., & Deng, W. (2021). Quantum differential evolution with cooperative coevolution framework and hybrid mutation strategy for large scale optimization. Knowledge-Based Systems, 224, 107080.

[12] Deng, W., Xu, J., Gao, X. Z., & Zhao, H. (2020). An enhanced MSIQDE algorithm with novel multiple strategies for global optimization problems. IEEE Transactions on Systems, Man, and Cybernetics: Systems.

[13] Deng, W., Xu, J., Zhao, H., & Song, Y. (2020). A novel gate resource allocation method using improved PSO-based QEA. IEEE Transactions on Intelligent Transportation Systems.

[14]Dragoni, M., Tettamanzi, A. G., & da Costa Pereira, C. (2015). Propagating and aggregating fuzzy polarities for concept-level sentiment analysis. Cognitive Computation, 7(2), 186-197.

[15]Dutta, A. K., & Sait, A. R. W. (2012). An application of intuitionistic fuzzy in routing networks. Editorial Preface, 3(6).

[16] Guo, S., Zhang, X., Du, Y., Zheng, Y., & Cao, Z. (2021). Path planning of coastal ships based on optimized DQN reward function. Journal of Marine Science and Engineering, 9(2), 210.

[17] Hassan, A., & Mahmood, A. (2017, April). Deep learning approach for sentiment analysis of short texts. In 2017 3rd international conference on control, automation and robotics (ICCAR) (pp. 705-710). IEEE.

[18]Huang, C. W., Lin, K. P., Wu, M. C., Hung, K. C., Liu, G. S., & Jen, C. H. (2015). Intuitionistic fuzzy c-means clustering algorithm with neighborhood attraction in segmenting medical image. Soft Computing, 19(2), 459-470.

[19] Jain, A., & Nandi, B. P. (2020). Intuitionistic and Neutrosophic Fuzzy Logic: Basic Concepts and Applications. In Hybrid Intelligent Systems in Control, Pattern Recognition and Medicine (pp. 3-18). Springer, Cham.

[20] Jain, A., Nandi, B. P., Gupta, C., & Tayal, D. K. (2020). Senti-NSetPSO: large-sized document-level sentiment analysis using Neutrosophic Set and particle swarm optimization. Soft Computing, 24(1), 3-15.

[21]Jefferson, C., Liu, H., & Cocea, M. (2017, July). Fuzzy approach for sentiment analysis. In 2017 IEEE international conference on fuzzy systems (FUZZ-IEEE) (pp. 1-6). IEEE.

[22]Jeong, Y. S., & Shin, S. S. (2018). Fast Fourier transform based efficient data processing technique for big data processing speed enhancement in P2P computing environment. Peer-to-Peer Networking and Applications, 11(6), 1186-1196.

[23]Ju, H., & Yu, H. (2018, January). Sentiment Classification with Convolutional Neural Network using Multiple Word Representations. In Proceedings of the 12th International Conference on Ubiquitous Information Management and Communication (p. 9). ACM.

[24]Kang, M., Ahn, J., & Lee, K. (2018). Opinion mining using ensemble text hidden Markov models for text classification. Expert Systems with Applications, 94, 218-227.

[25]Krishna, B. V., Pandey, A. K., & Kumar, A. S. (2018). Feature based opinion mining and sentiment analysis using fuzzy logic. In Cognitive science and artificial intelligence (pp. 79-89). Springer, Singapore.

[26] Liu, B., Blasch, E., Chen, Y., Shen, D., & Chen, G. (2013, October). Scalable sentiment classification for big data analysis using naive bayes classifier. In 2013 IEEE international conference on big data (pp. 99-104). IEEE.

[27]Liu, Y., Bi, J. W., & Fan, Z. P. (2017). Multi-class sentiment classification: The experimental comparisons of feature selection and machine learning algorithms. Expert Systems with Applications, 80, 323-339.

[28]Nagarajan, S. M., & Gandhi, U. D.(2018).Classifying streaming of Twitter data based on sentiment analysis using hybridization. Neural Computing and Applications, 1-9.

[29]Naseem, U., Razzak, I., Musial, K., & Imran, M. (2020). Transformer based deep intelligent contextual embedding for twitter sentiment analysis. Future Generation Computer Systems, 113, 58-69.

[30]Ohana, B., & Tierney, B. (2009, October). Sentiment classification of reviews using SentiWordNet. In 9th. it & t conference (Vol. 13, pp. 18-30).

[31]Parchami, M., Zhu, W. P., Champagne, B., & Plourde, E. (2016). Recent developments in speech enhancement in the short-time Fourier transform domain. IEEE Circuits and Systems Magazine, 16(3), 45-77.

[32]Phu, V. N., Dat, N. D., Tran, V. T. N., Chau, V. T. N., & Nguyen, T. A. (2017). Fuzzy C-means for english sentiment classification in a distributed system. Applied Intelligence, 46(3), 717-738.

[33] Ruz, G. A., Henríquez, P. A., & Mascareño, A. (2020). Sentiment analysis of Twitter data during critical events through Bayesian networks classifiers. Future Generation Computer Systems, 106, 92-104.

[34]Salvetti, F., Lewis, S., & Reichenbach, C. (2004). Automatic opinion polarity classification of movie reviews. Colorado research in linguistics, 17(1), 1.

[35] Song, C., Wang, X. K., Cheng, P. F., Wang, J. Q., & Li, L. (2020). SACPC: A framework based on probabilistic linguistic terms for short text sentiment analysis. Knowledge-Based Systems, 194, 105572.

[36]Sharma, A., & Dey, S. (2012). A document-level sentiment analysis approach using artificial neural network and sentiment lexicons. ACM SIGAPP Applied Computing Review, 12(4), 67-75.

[37]Tang, D., Qin, B., & Liu, T. (2016). Aspect level sentiment classification with deep memory network. arXiv preprint arXiv:1605.08900.

[38]Tripathy, A., Anand, A., & Rath, S. K. (2017). Document-level sentiment classification using hybrid machine learning approach. Knowledge and Information Systems, 53(3), 805-831.

[39] Vashishtha, S., & Susan, S. (2019). Fuzzy rule based unsupervised sentiment analysis from social media posts. Expert Systems with Applications, 138, 112834.

[40]Vashishtha, S., & Susan, S. (2021). Highlighting keyphrases using senti-scoring and fuzzy entropy for unsupervised sentiment analysis. Expert Systems with Applications, 169, 114323.

[41]Wang, J., Yu, L. C., Lai, K. R., & Zhang, X. (2016, August). Dimensional sentiment analysis using a regional CNN-LSTM model. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers) (pp. 225-230).

[42]Wang, J., Zhao, H., Xu, J., Li, H., Zhu, H., Chao, S., & Zheng, C. (2018). Using Intuitionistic Fuzzy Set for Anomaly Detection of Network Traffic from Flow Interaction. IEEE Access, 6, 64801-64816.

[43]Yang, M., Qu, Q., Chen, X., Guo, C., Shen, Y., & Lei, K. (2018). Feature-enhanced attention network for target-dependent sentiment classification. Neurocomputing, 307, 91-97

[44]Yessenalina, A., Yue, Y., &Cardie, C. (2010, October). Multi-level structured models for document-level sentiment classification. In Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing (pp. 1046-1056).Association for Computational Linguistics.

[45]Zadeh, L. A. (1965). Fuzzy sets. Information and control, 8, 3.

[46] Zhan, J., Ye, J., Ding, W., & Liu, P. (2021). A novel three-way decision model based on utility theory in incomplete fuzzy decision systems. IEEE Transactions on Fuzzy Systems.

[47]Zhang, M., Zhang, Y., & Vo, D. T. (2016, March). Gated neural networks for targeted sentiment analysis. In Thirtieth AAAI Conference on Artificial Intelligence.

[48]Zhang, D., Liao, X., Yang, B., & Zhang, Y. (2018). A fast and efficient approach to color-image encryption based on compressive sensing and fractional Fourier transform. Multimedia Tools and Applications, 77(2), 2191-2208.

[49]Zhang, K., Zhan, J., & Wu, W. Z. (2020). On multi-criteria decision-making method based on a fuzzy rough set model with fuzzy α-neighborhoods. IEEE Transactions on Fuzzy Systems.

[50] Zhan, J., Jiang, H., & Yao, Y. (2020). Three-way multi-attribute decision-making based on outranking relations. IEEE Transactions on Fuzzy Systems.