A CONTEMPORARY REVIEW ON ASPECT-BASED SENTIMENTAL ANALYSIS

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Abstract : ***Social media sites are gaining popularity across the world and they are being used in every sphere of life. Even, in India social media platforms are being used for all purposes ranging from movie reviews to political campaigns to digital marketing of products. One key application of social media which is under tremendous research is the sentimental analysis of users. As most of the people are active on the social networking sites and are using these platforms to launch their emotions about any specific product or service or even idea; hence sentimental analysis is the vital and focal point of research. Prior to purchase a product or service, consumers frequently surf the Web for expert reviews, but progressively also for suggestions of other consumers, expressed in blogs, social networks etc. Many useful suggestions are exhibited in text-only form (like in tweets). It is then prudent to extract aspects (like screen, battery) from the texts that discuss a particular entity (like a smartphone), i.e., sort out what is being discussed, and also estimate aspect sentiment scores, polarity i.e., how negative or positive the sentiment for each aspect is. These two goals are jointly termed as Aspect Based Sentiment Analysis. This review is based on this Aspect-based sentimental analysis concept.***

IndexTerms - Aspect, Sentiment Analysis, NLP, Social Media, Machine Learning.

I. INTRODUCTION

Social media platforms and, in particular, microblogging services such as Twitter, Tumblr, and Weibo are increasingly being adopted by users to access and publish information about a great variety of topics. These new mediums of expression enable people to connect to each other, and voice their opinion in a simple manner[1]. Sentiment analysis or opinion mining refers to the application of techniques from fields such as natural language processing (NLP), information retrieval and machine learning, to identify and extract subjective information from textual datasets [2].

One of the most popular sentiment analysis tasks is the automatic classification of documents or sentences into sentiment categories such as positive, negative, and neutral. These sentiment classes represent the writer's sentiment toward the topic addressed in the message. Sentiment analysis applied to social media platforms has received increasing interest from the research community due to its importance in a wide range of fields such as business, sports, and politics. Several works claim that social phenomena such as stock prices, movie box-office revenues, and political elections, are reflected by social media data [3][4] and that opinions expressed in those platforms can be used to assess the public opinion indirectly[5].

II. MACHINE LEARNING

If computer science is the systematic characterization of the computations that we can perform efficiently, what, then, is machine learning? To solve a problem with a computer, one first designs an appropriately efficient algorithm that solves the problem and then implements that algorithm in hardware or software. If we cannot specify the algorithm, then we cannot solve the problem with direct programming. Machine learning extends what we can do with computers by letting us solve problems even when we are unable to manually design an algorithm to solve them. Using examples of correct behaviour, we can specify an algorithm non-constructively. Thus a machine learning algorithm is a meta-algorithm for creating algorithms from data that defines what they should produce.

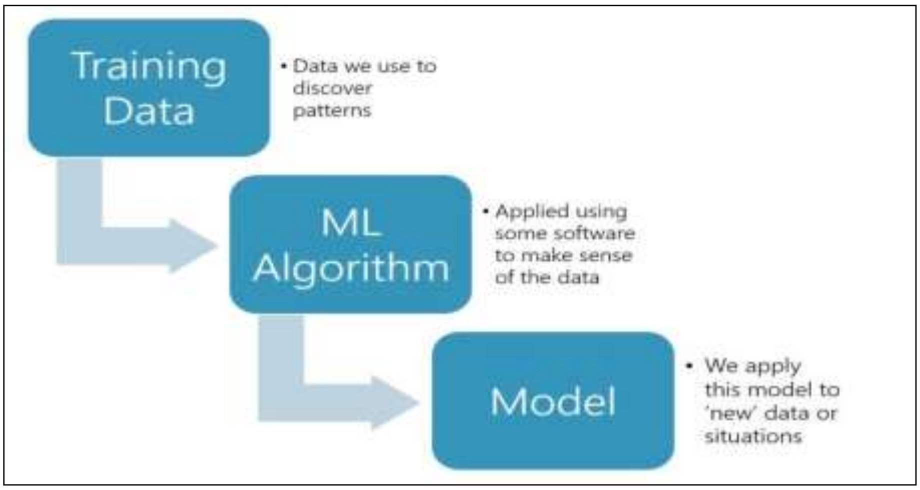

Fig. 1: Working of Machine Learning[6]

Meta-algorithms give us a powerful new way of interacting with computers by telling them what they should compute instead of how they should compute it. Extending our ability to solve problems with computers is reason enough to study machine learning, but it is far from the only reason. Just as studying learning helps us understand what we can practically compute, we must also study computation in order to inform our understanding of learning.

Machine learning as a scientific discipline examines the computational basis of learning; thus it is essential even if we are only interested in how humans and animals learn. These two central motivations support each other. Trying to solve problems using computational models of learning sheds light on our understanding of the brain, and, by the same token, what we learn about the brain can serve as inspiration for designing learning machines. Basically, Machine Learning allows to tackle problems (tasks) that don’t have an exact solution like recommendations, predictions or clustering.

Studying machine learning has scientific value both as a way to understand computation and as a way to understand learning, but for science to matter it must have a positive impact on the world. By always maintaining a connection to important practical problems, one increases the chance that their research on machine learning will have such a positive impact. One great property of the field of machine learning is that its methods can help us solve many specific problems of practical and commercial interest. However, if as researchers our only concern is making scientific progress, should we still labour over specific applications of our more general methods? Obviously we need to try new methods on actual problems to make sure that they work, but perhaps we can start with a new method and then look for problems it can attack.

Alternatively, we can start with a problem and then do whatever it takes to solve it; sometimes solving a problem will require new methods and sometimes not, but in either case good research will help us learn the limitations and advantages of existing methods as well as what aspects of the problem are important.

III. Natural Language Processing

With the growth of computers and internet, computer linguistics has become an imperative field. Basically computational linguistics began soon after the development of the first computers. This area of Artificial Intelligence which explores how computers can be made to understand and manipulate natural language text or speech to do incredible improvement in communication is known as Natural Language Processing. NLP will not only perk up communication between humans and computers, but also communiqué between computers and computers. The aim of NLP is to enhance ability of computers to extract valuable information and to improvise it like a human expert will do.

Natural language processing (NLP) has fascinated researchers since the advent of AI as a discipline in the 1950s, appearing both in philosophical arguments about the nature of intelligence and in applications. In fact, Turing proposed his famous imitation game that required a computer to communicate in human language only a few years before the first machine translation demo. Human language seems to be an important distinction between humans and other animals making language processing tasks natural members of the AI-set. Beyond any potential implications for AI research, software able to extract useful information from text automatically is of immense practical value simply because of the ubiquity of natural language text on the internet.

Text data have very different qualitative properties than data from other modalities and these properties provide important challenges for machine learning. Tokens, characters, and words are inherently discrete whereas pixel values are discrete merely because of digital quantization. Zipf distributions abound in NLP and the large fraction of words that are rare words demands machine learning models with powerful generalization abilities. Unlabelled data are often plentiful, but even in the largest unlabelled text corpora many particular constructions or phrases of interest will still only occur rarely. Human users also have very high standards for correctness and precision for text processing systems since an error in a single word can have non-local effects on the meaning of an utterance. Because massive collections of text data provide exciting opportunities for machine learning research, there is an extensive literature on natural language processing[7].

IV. Literature Review

M. Bouazizi & T. Ohtsuki[8] state that although opinion mining and sentimental analysis of social networking sites are undergoing immense research. However, most of the researchers ignore the bigger picture and are binary or ternary classification based i.e. considering user view as either positive, negative or neutral. The authors focus on multi-class classification i.e. seven different classes for matching user’s exact sentiment. For this, a graphical-user interface (SENTA) has also been developed by authors which provides ease of use and better understanding. The experimental results show that 81.3% accuracy has been achieved in the case of binary or ternary classification and a solid 60.2% accuracy even in the case of multi-class classification of user views.

Y. Wu et. al[9] discuss that the emerging size of social media data is a boon not only for the solution providers (or data owners), but also for the end users. This colossal availability of social media data can help the end users achieve a great understanding of society, however it working contrarily. This is where “visual analytics” to aid the common man to fully exploit this variable and immensely-sized multimedia social data. The authors have divided the available state-of-art techniques into two wide categories: information gathering and understanding user conduct. A comprehensive survey is also proposed by the authors here to fully undermine the structured and unstructured social media analysis techniques.

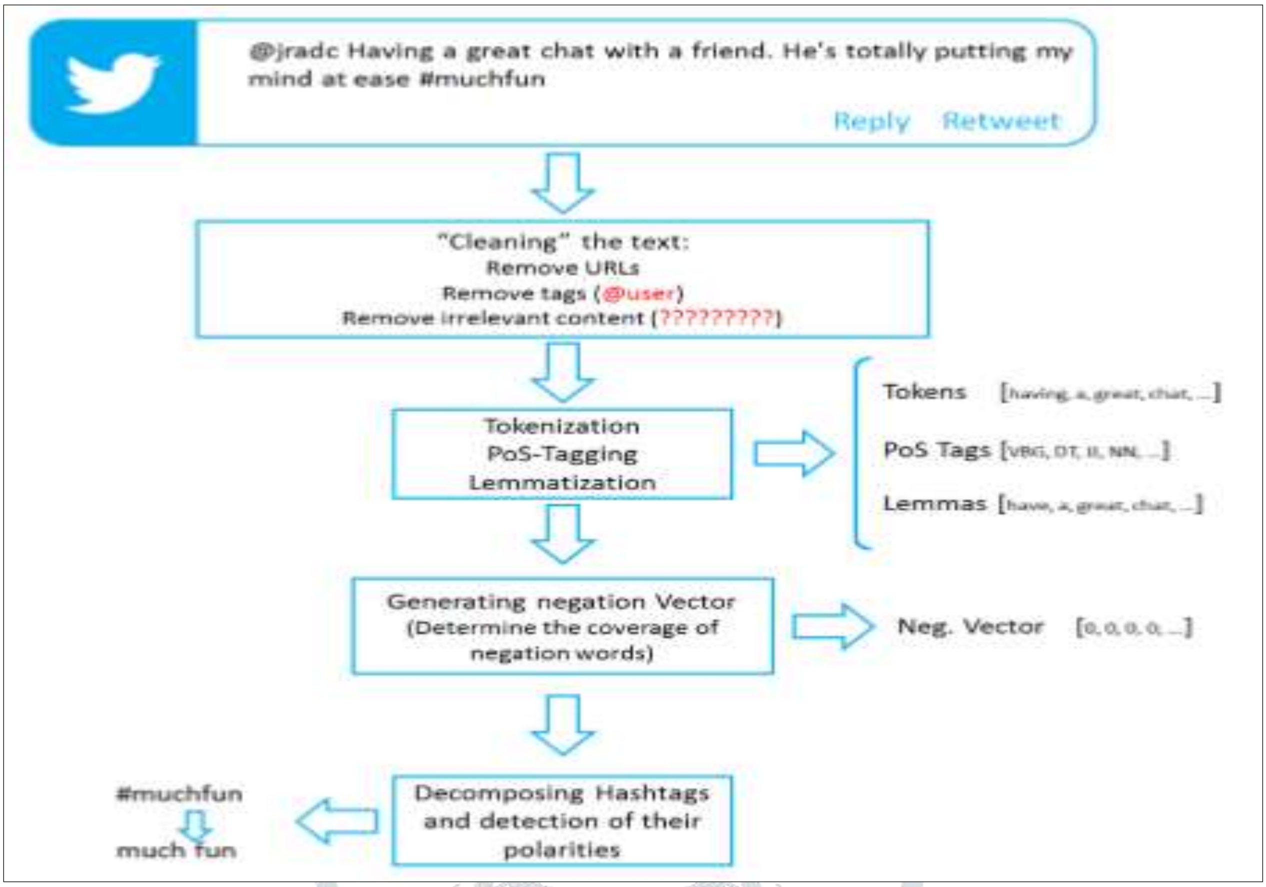

Fig 2: Working of SENTA (GUI tool) for Multi-class Classification[8]

X. Zhou et. al[10] address a grave problem of recognizing anonymous users which seem identical but are present widely on the social media platforms. Due to availability of user profiles publicly, duplication and personification of users for varied purposes is present extensively, hence using a cross-platform approach to identify such users will prove to be a prodigious benefit both in theory and practice of social computing.

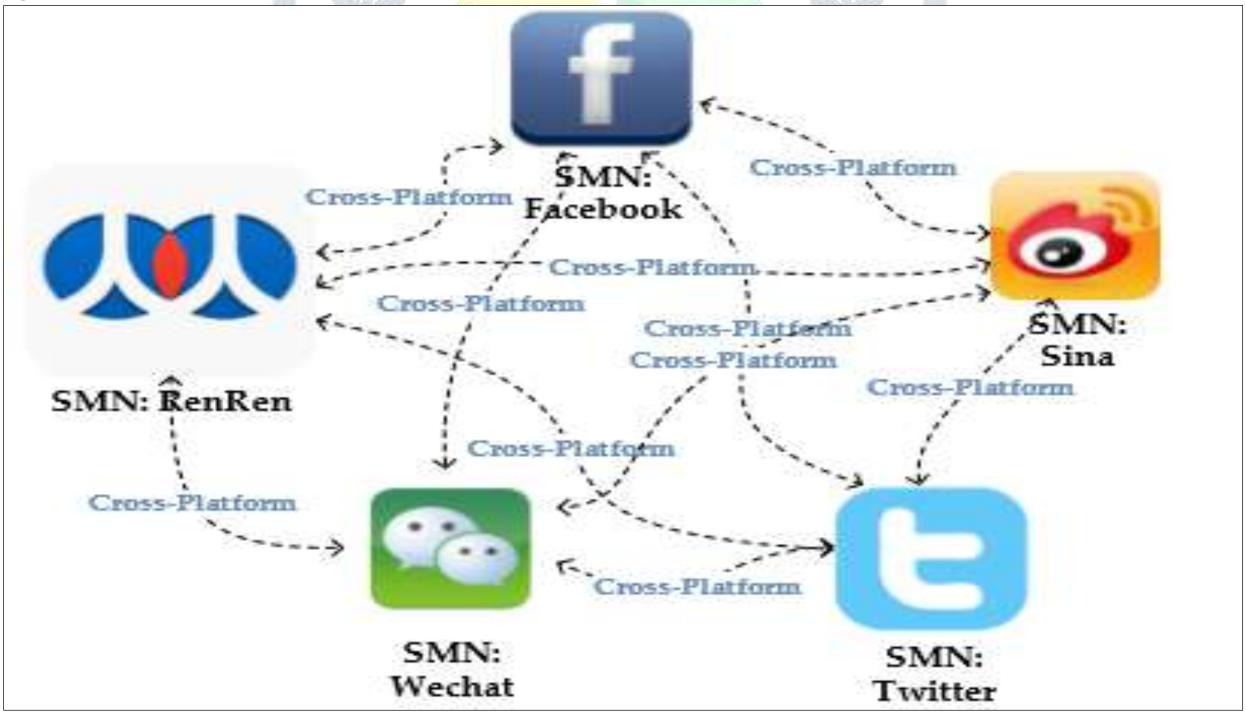

Fig 3: Cross-platform research to merge a variety of SMNs[10]

However, the present methodologies implementing user's location, writing pattern and network structure for distinguishing anonymous users are not yielding the expected results. Hence, the authors propose a novel method for the same i.e. Friend Relationship-Based User Identification (FRUI) algorithm which is based on the concept that no two users on the social networking sites share the same friendship cycle unless they are the same person.

N. D. Doulamis et. al[11] focus on a specific social micro-blogging site Twitter and gave a particular approach to detect the vital events on Twitter. The twitter events could be short-timed (trending currently) or long-timed (submitted recently) and their identification could yield superior structuring of user content. As the conventional techniques available seem inadequate, a fuzzy-based model is developed by the eminent authors to entirely capture real-life data and twitter dynamics. In addition to it, a word-clustering graph has also been implemented to properly identify an event.

N. Cao et. al[12] have worked on an ingenious concept that is detecting anomalous users present on the social media networks and for this herculean task they have deployed unsupervised learning techniques. The paper also discusses how the visualization techniques can be used for better understanding of user social behavior depending upon user's social relations and communication. Keeping all the above points in mind, TargetVue – a system is developed for anomaly detection, which is depicted as follow:

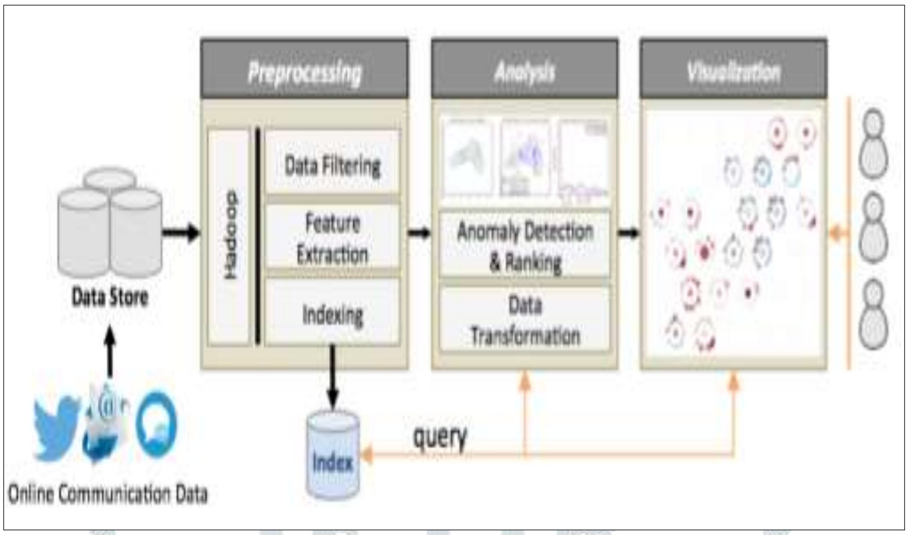

Fig 4: Working of TargetVue – the anomaly detection system[26]

Y. Zhang et. al[13] concentrated on a vital area of social media which is the security aspect. The authors have taken Twitter as a case example of social networking sites and have analysed how the trending topics in Twitter is affecting people's behaviour and mood. Twitter trends are very popular these days and if in hands of wrong people, they may use social sites for spreading hate and hate crimes, which will be a curse for the society. It was also found out that there are numerous fake accounts on Twitter and spammers use them for their own advantage i.e. manipulating the trending topics, hence highlighting the news they want for money or for fun or with bad intentions.

Z. Liu & B.J. Jansen[14] have focused on the information seeking part of the social media networks and have traced that it's a natural drift in a mundane man's life to go to social network sites for searching information. All the vital sites such as Facebook, Twitter, etc. help their users to join specific groups in which they are interested in and such groups notify their members of all the vivacious information on a given subject. The question classification has been done on two basis: subjective and objective. Based on this classification, a predictive model has been proposed to instigate the subjectivity orientation of user questions.

G. I. Parisi et. al[15] have established the idea of lifelong learning through novel deep learning methods. The traditional deep learning approaches focus on the supervised pattern where a group of training data is already given to the machine based upon which it classifies things and learn, however a new method is required for action recognition from videos. This could be achieved with the help of self-organizing deep neural architectures, which in turn uses unsupervised learning methodologies through recurrent neural networks which are arranged hierarchically.

M. Bouazizi & T. Ohtsuki[16] present a brilliant and challenging idea of using machine learning for detecting sarcasm in tweets. Sarcasm represents soft irony in the language, which is hard to detect even by humans, hence it could be a daunting task for the computer. The authors have proposed a pattern-based tactic for sarcasm analysis through which they can categorize each tweet as sarcastic or non-sarcastic. To achieve their target, the Weka tool is used in conjunction with the Libsvm. The experimental results have shown greater efficiency upto 83.1%, which is way better than the state-of-art technologies.

J. Lin and A. Kolcz[17] have tried to bundle Twitter with Hadoop-based, Pig-centric analytics platform. As data is increasing globally at a tremendous rate, so does the data warehousing and data mining techniques. One such platform is Pig, which not only provides the predictive capability but also the analytic capabilities for huge data available. It is stated that the common tasks involved in social sites analysis can be easily implemented with the help of Pig platform, which is also open-source. This paper uses a supervised model for training of the machine.

V.Carchiolo et. al[18] brought a new application of social media sentimental analysis. They suggest that the Twitter can be used as a tool to predict the health related issues and diseases' dynamics. As the health data from hospitals and health centres is not easily available because of various legal and ethical constraints, Twitter can be used as a tool for collection of such data. After the data collection, this data undergoes the numerous machine learning and Natural language processing tools to predict the concern and spread of a disease in a specific geographical area. The whole process mentioned above is shown below:

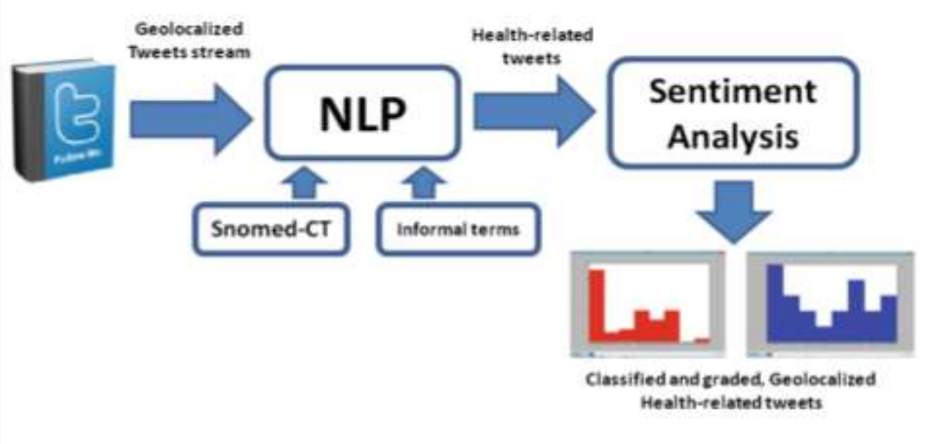

Fig 5: Application Architecture to study Dynamics of Diseases through Twitter[18]

H. Anber et. al[19] have got new insights on the sentimental analysis done with the help of Twitter. Myriad social media networks like Facebook, Twitter, Instagram, Linkedin behave in dissimilar ways and to distinguish each, authors have considered two major factors: Homophily and Reciprocity. Homophily refers to the tendency of contacting similar users at a higher rates than other and Reciprocity refers to the relation of following a user and getting followed back. Like in Facebook, if a user is friend with someone, they relation is reciprocal i.e. both are each other's friend, but in Twitter relationship is mostly following updates from a celebrity and thus mostly unidirectional. Depending upon this, Tweets can be used to analyse the social behaviour towards any social event.

M. Ben-Ari & F. Mondada[20] have published a detailed article on how the machine learning basically works. They have used statistical techniques primarily Linear Discriminant Analysis (LDA) based on the supervised learning approach. LDA is a kind of a classification algorithm of machine learning which is helpful in detecting patterns and also to forecast outcomes without explicit programming. This is a how an artificially intelligent robotic arm can be used to distinguish between balls of different colours.

L. Jiang et. al[21] too have taken the case study of miscro-blogging site – Twitter for sentimental analysis. Usually a binary classification of tweets is done i.e. marking them as positive or negative, however this is target-independent strategy which is not full-proof. Hence, a target-dependent strategy is needed to fill in the gaps, which decides by taking not just 1 tweet, but all the related tweets into account. The experimental results show that the target-dependent approach is much better than the target-independent one.

M. Pennacchiotti & A.M. Popescu[22] have proved the worth of Natural Language Processing in the Twitter Sentimental Analysis. Their approach is taking three key points into consideration which are political orientation, soft corner for a particular business and ethnicity for user classification. All the above mentioned features can be predicted considerably well by careful consideration of linguistic aspects of user tweets, tweet content and their respective behaviour on Twitter. Here, the Latent Dirichlet Allocation (LDA) model is used primarily for the linguistic characteristics.

H. Becker et. al[23] have tried to characterize the social media platforms especially Twitter (because of its short messaging feature) for identification of real-events. For this, they have taken into account millions of tweets (nearly 2,600,000 tweets) and have used machine learning approach to classify them as event-based or non-event based tweets. An online-clustering technique that groups together similar tweets about a real event are grouped together. Based upon this several key factors can be improved like prioritization, filtering of content and ranking of events.

P. Juneja and U. Ojha[24] suggest that if Twitter Sentimental Analysis can be used to predict the market trends or fashion trends, then they can also be used for prediction of elections. The research in this paper is twofold: one aspect is based on whether Twitter can be used to predict the outcomes of Delhi Corporation Elections and other feature compares all the available social media classifiers to identify the best tool for it. The investigational outcomes show that Multinomial Naïve Bayes classifier is the most accurate sentiment predictors with 78%. Also, depending upon various political events like rallies or speeches, the sentiments of public get inclined towards a political party.

G. Gautam & D. Yadav[25] advocate that Twitter Sentimental Analysis is also a major tool for classification of user reviews. So, they have used machine learning approach with semantic analysis for classifying the tweets and user reviews about a particular product. The procedure described here is first pre-processing the available dataset, then extract the feature vector (adjective), finally apply copious classification algorithms and compare their results.

P. Kumar et. al[26] state that Twitter as a data analysis tool is under-utilized. Only, two chief territories are pulling in more enthusiasm for the examination group, the feeling mining and assessment investigation. An assessment examination of general's conclusions mined from the well known smaller scale blogging site Twitter is performed. The real accentuation of this paper is set on assessing precision of various machine learning calculations for the errand of twitter notion investigation.

K. Kang et. al[27] contributed immensely by detecting user's psychological states through the user tweets. In this context, the authors have taken into account not only text, but also other multimedia like images, emoticons, etc. to identify the depressive users. Apart from this the tweets of depressive and non-depressive users are analysed to clearly distinguish their characteristics. Identification of depressive users can predict the mood swings of users and ultimately prevent possible suicides.

E. Chaniotakis & C. Antoniou[28] state that social networking sites are used in every sphere of life including transportation. With the help of its myriad characteristics like combining temporal, textual and spatial information from social media, continuous information flow, message content, etc. a colossal amount of information can be generated which can be analysed to delineate hidden patterns regarding rider's satisfaction and examination of the relationship between mobility and social media networks.

G. T. Giancristofaro & A. Panangadan[29] have integrated the textual as well as image data for the sentimental analysis for the purpose of transportation studies. The social media platform used here is Instagram and also takes into account California Department of Transportation (Caltrans). Numerous features like comment data, captions and images are submitted to the machine learning network, so that the prediction of sentiments regarding transportation. The classification accuracy reaches close to reported human classification agreement (approximately 80%). This indicates that transportation agencies can completely automate the process of gauging public sentiment toward their services and performance from multimedia based social media sources. However, the results do not indicate that visual features are more informative than text features.

V. Summary and Discussion

Table I: Summary of Research Work

Author	Year	Source	Major Contribution
M. B. Ari and F. Mondada[20]	2018	Springer	Using LDA in supervised learning
M. Bouazizi and T. Ohtsuki[8]	2017	IEEE Translations	Multi-class Sentimental Analysis
P. Juneja and U. Ojha[24]	2017	8th ICCCNT Conference	Analysing Twitter to predict 2014 elections
E. Chaniotakis & C. Antoniou[28]	2016	IEEE Intelligent Systems	Relationship between social media and transportation
G. T. Giancristofaro and A. Panangadan[29]	2016	19th ITSC Conference	Analysing Instagram data for California Department of Transportation
H. Anber, A. Salah and A. A. Abd El-Aziz[19]	2016	IJCEE	Analysing sentiments based on Homophily and Reciprocity
K. Kang, C. Yoon and E. Y Kim[27]	2016	IEEE Conference	Identifying depressive users through social media
M. Bouazizi and T. Ohtsuki[16]	2016	IEEE Tranlations	Sarcasm detection
P. Kumar, T. Choudhury, S. Rawat and S. Jayaraman[26]	2016	IEEE Conference	Assessing precision of various machine learning calculations
Y. Zhang, X. Ruan, H. Wang, H. Wang and S. He[13]	2016	IEEE Transactions	How mischievous people spread hate crimes through Twitter
Z. Liu and B. J. Jansen[14]	2016	IEEE Transactions	Difference between subjective and objective questions
N. Cao, C. Shi, S. Lin, J. Lu, Y.R Lin and C. Y Lin[12]	2015	IEEE Transactions	Classifying user's behaviour
N. D Doulamis, D. Anastasios, D. Doulamis, P. Kokkinos and E. M Varvarigos[11]	2015	IEEE Transactions	Detecting various vital events (both short-timed and long-timed)
V. Carchiolo, A. Longheu, and M. Malgeri[18]	2015	Springer	Extraction of health related information
X. Zhou, X. Liang, H. Zhang and Y. Ma[10]	2015	IEEE Transactions	Identifying anonymous identical users on different social platforms
G. Gautam and D. Yadav[25]	2014	IEEE	Classifications of user sentiments in Twitter
J. Lin and A. Kolcz[17]	2012	ACM	Use of open-source platform for data mining
H. Becker, M. Naaman and L. Gravano[23]	2011	5th AAAI Conference	Identifying real events through Twitter
L. Jiang, M. Yu, M. Zhou, X. Liu and T. Zhao[21]	2011	ACL	Target dependent sentimental analysis
M. Pennacchiotti and A.M	2011	5th AAAI	Using NLP in sentiment analysis

Popescu[22]		Conference	
Y. Wu, N. Cao, D. Gotz, Y. P Tan and D. A. Keim[9]	1997	IEEE Transactions	Using visual analytics to help to exploit vastly available data

VI. CONCLUSIONS

This research paper reviews the recent work done on the current hot topic "Sentimental Analysis" and the crux of study are the following. The actual sentiment conveyed by a word depends on subjective judgment of a person, which is hard to diagnose by a machine. Social networking sites use a lot of informal words or slangs. This rich diversity makes the opinion mining and sentimental analysis task a herculean one both in terms of time as well as cost. Use of sarcasm both in terms of words or even emoticons is hard to infer. Most of the research on sentimental analysis is based on binary opinions (positive or negative) or ternary opinions (positive, negative or neutral) only, however most of the scholarly work ignores the aspect-based part of opinions.

REFERENCES

[1] B. J. Jansen, M. Zhang, K. Sobel and A. Chowdury, "Twitter power: Tweets as electronic word of mouth", Journal of the American Society for Information Science and Technology, vol. 60, no. 11, 2009, pp. 2169–2188.

[2] B. Pang and L. Lee, "Opinion mining and sentiment analysis. Foundations and Trends in Information Retrieval", Foundations and trends in information retrieval, vol. 2, no. 1, 2008, pp. 1–135.

[3] J. Bollen, H. Mao and X.J Zeng, "Twitter mood predicts the stock market", Journal of computational science, vol. 2, no. 1, 2011, pp. 1–8.

[4] S. Asur and B.A. Huberman, "Predicting the future with social media", Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, vol. 1, Washington, DC, USA: IEEE Computer Society, 2010, pp. 492–499.

[5] B. O'Connor, R. Balasubramanyan, B.R Routledge and N.A Smith, "From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series", Proc. Fourth International AAAI Conference on Weblogs and Social Media, AAAI Press, 2010, pp. 122–129.

[6] "AI and Machine Learning in finance - are we doomed?". [Online]. Available: http://www.linkedin.com/pulse/ai-machine-learning-finance-we-doomed-sanjay-bhandari. [Accessed: Jan. 19, 2003]

[7] A. Kaushik and A. Kumar, "A Novel Solution based Approach to NLP", International Conference on Reliability, Infocom Technology and Optimization(ICRITO), Lingaya's University, Faridabad, Nov 2010.

[8] M. Bouazizi and T. Ohtsuki, "Pattern-Based Approach for Multi-Class Sentiment Analysis in Twitter", vol. 5, no. 7, IEEE Translations and Content Mining, August 18, 2017, pp. 20617 – 20639.

[9] Y. Wu, N. Cao, D. Gotz, Y. P Tan and D. A. Keim, "A Survey on Visual Analytics of Social Media Data", IEEE Transactions on Multimedia, DOI 10.1109/TMM.2016.2614220, 2016. Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specification, IEEE Std. 802.11, 1997.

[10] X. Zhou, X. Liang, H. Zhang and Y. Ma, "Cross-Platform Identification of Anonymous Identical Users in Multiple Social Media Networks", IEEE Transactions on Knowledge And Data Engineering, DOI 10.1109/TKDE.2015.2485222, 2015.

[11] N. D. Doulamis, D. Anastasios, D. Doulamis, P. Kokkinos and E. M Varvarigos, "Event Detection in Twitter Microblogging", IEEE Transactions on Cybernetics, 2015.

[12] N. Cao, C. Shi, S. Lin, J. Lu, Y.R Lin and C. Y Lin, "TargetVue: Visual Analysis of Anomalous User Behaviors in Online Communication Systems", IEEE Transactions on Visualization And Computer Graphics, vol. 22, no. 1, Jan. 2016, pp. 280-289.

[13] Y. Zhang, X. Ruan, H. Wang, H. Wang and S. He, "Twitter Trends Manipulation: A First Look Inside the Security of Twitter Trending", IEEE Transactions on Information Forensics And Security, 2016.

[14] Z. Liu and B. J. Jansen, "Understanding and Predicting Question Subjectivity in Social Question and Answering", IEEE Transactions on Computational Social Systems, vol. 3, no. 1, Mar. 2016.

[15] G. I. Parisi, J. Tani, C. Weber and S. Wermter, "Lifelong learning of Human actions with deep neural network self-organization", Elsevier Neural Networks, vol. 96, 2017, pp. 137-149.

[16] M. Bouazizi and T. Ohtsuki, "A Pattern-Based Approach for Sarcasm Detection on Twitter", IEEE Translations and Content Mining, 2016.

[17] J. Lin and A. Kolcz, "Large-Scale Machine Learning at Twitter", SIGMOD '12, Copyright ACM 978-1-4503-1247-9/12/0, May 20–24, 2012, Scottsdale, Arizona, USA, pp. 793-804.

[18] V. Carchiolo, A. Longheu, and M. Malgeri, "Using Twitter Data and Sentiment Analysis to Study Diseases Dynamics", Springer International Publishing, ITBAM2015, Switzerland, 2015, pp. 16-24.

[19] H. Anber, A. Salah and A. A. Abd El-Aziz, "A Literature Review on Twitter Data Analysis", International Journal of Computer and Electrical Engineering, vol. 8, no. 3, June 2016, pp. 241-249.

[20] M. B. Ari and F. Mondada, "Machine Learning - Elements of Robotics", 2018.[Online] Available: https://doi.org/10.1007/978-3-319-62533-1_14. [Accessed: Dec. 24, 2017].

[21] L. Jiang, M. Yu, M. Zhou, X. Liu and T. Zhao, "Target-dependent Twitter Sentiment Classification", Proc. of the 49th Annual Meeting of the Association for Computational Linguistics, Portland, Oregon, June 19-24, 2011, pp. 151–160.

[22] M. Pennacchiotti and A.M Popescu, "A Machine Learning Approach to Twitter User Classification", Fifth International AAAI Conference on Weblogs and Social Media, 2011, pp. 281-288.

[23] H. Becker, M. Naaman and L. Gravano, "Beyond Trending Topics: Real-World Event Identification on Twitter", Fifth International AAAI Conference on Weblogs and Social Media, 2011, pp. 438-441.

[24] P. Juneja and U. Ojha, "Casting Online Votes:To Predict Offline Results (Using Sentiment Analysis by machine learning Classifiers)" , 8th ICCCNT 2017, July 3-5, 2017, IIT Delhi, Delhi, India, 2017.

[25] G. Gautam and D. Yadav, "Sentiment Analysis of Twitter Data Using Machine Learning Approaches and Semantic Analysis", 978-1-4799-5173-4/14/$31.00 © IEEE, 2014.

[26] P. Kumar, T. Choudhury, S. Rawat and S. Jayaraman, “Analysis of Various Machine Learning Algorithms for Enhanced Opinion Mining using Twitter Data Streams”, 2016 IEEE International Conference on Micro-Electronics and Telecommunication Engineering, 2016, pp. 265-270.

[27] K. Kang, C. Yoon and E. Y Kim, “Identifying Depressive Users in Twitter Using Multimodal Analysis”, IEEE BigComp 2016, 2016, pp. 231-238.

[28] E. Chaniotakis and C. Antoniou, “Mapping Social Media for Transportation Studies”, IEEE Intelligent Systems, 2016.

[29] G. T. Giancristofaro and A. Panangadan, “Predicting Sentiment toward Transportation in Social Media using Visual and Textual Features”, 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), Windsor Oceanico Hotel, Rio de Janeiro, Brazil, November 1-4, 2016, pp. 2113-2118.