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Knowledge Representation and Reasoning for Sponsor Analysis in Sports on Stock Market

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ABSTRACT: The nonprofit investors use twitter to build relationships with online stakeholders, while cultivating new audiences through sponsorships. This paper examines the relationship between the company sponsors for promoting their product and the messages obtained on follower base based on the Bidirectional Gated Recurrent Unit-Recurrent Neural Network (Bi-GRU-RNN) The tweets are analyzed in the advocacy campaign to uncover what relationship, exists between the online communication function employed and the amount of attention a tweet receives. Further analysis examines the marketing potential of other user's tweets about the sports persons in the cricket. The popularity obtained from the audience for the sportsman dramatically develops faith in sponsor of the companies for promoting their brand. The popularity nowadays is gained through the social Medias such as Twitter, Facebook etc. The results showed an analysis of stock market price on the product based on the popularity gained for the sports person. The results obtained from the proposed method clearly ease the sponsors to select the sportsman based on the performance as well as on huge fan base who tweets and expresses their fandom through the site. This in turn acts a financial tool for developing the stock price and shows an improvement in the stock market.

KEYWORDS: Branding, Bidirectional Gated Recurrent Unit, Recurrent Neural Network, Sponsorships, Stock market, Twitter

I. INTRODUCTION

Social media are increasingly seen as potential gold mines for creating insights on the performance organizations. Despite the hype in the market, organizations face several uncertainties on how to seize the opportunities and to use social media platforms. Analyzing data to judge the performance of an organization is the primary area of business intelligence. Typically, a business intelligence approach requires models that operationalize a company's strategy and business model [1, 2]. Scholarly research on social media and its marketing communications role within the sport industry is rapidly expanding. Research on this topic till date has focused on consumer responses to sport-related social media messages through social media. The sport organizations performed various acts to engage fans in the sport events. The popularity is gained for the athlete and reviews regarding their favorite athlete is available in web domains such as Facebook and Twitter [3, 4]. According to the behavioral finance theory, researchers have shown that the emotions of market participants will have a strong influence on the stock market through the social media. The role that investor sentiment plays in asset pricing has shown its great importance in financial economics. Various investor sentiment proxies have been investigated the contemporaneous correlations between investor sentiment and market wide variables [5-8]. In numerous recent studies, mood levels have been used as a proxy for investor sentiment. According to these findings, mood states can spread among Internet users through text based communication. In this research we utilize the brand relationship theory perspective, which maintains that by acting as identity-expressing symbols, brands acquire stereotypical images and identities (personalities) in consumer minds, which helps position them as social relationship partner [9,10]. In our study, a sentiment index to capture the sentiment of investors and news media. Our goal is to categorize a tweet based on the behavior aspects, popularity aspects and financial aspects on the stock market price.

This research paper is pre-arranged as follows. In section 2, numerous research utilized twitter as a tool for developing stock market price in the sports field are reviewed. Detailed explanation about the proposed system is given

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in section 3. In addition, section 4 illustrates about the evaluation of the results and comparative analysis of the proposed system. The conclusion is made in section 5.

II. LITERATURE REVIEW

The companies approach athletes as their ambassador for representing their companies to sell their goods in the form of sponsorships. The popularity obtained from the audience for the sportsman dramatically develops faith in sponsor of the companies for promoting their brand. The popularity nowadays is gained through the social medias such as Twitter, Facebook etc., Here are few survey regarding the tweets received from the audience to the athlete that in turn reflects on the athlete to be a part of their brand thereby improving the stock price financially.

Jin, X., *et* al., [11] examined the stock market behavior for a long-lived subset of firms in Shanghai and Shenzhen CSI 300 Index (CSI 300 Index) both before and after the establishment of firms' Microblogging in Sina Weibo. The empirical results show a significant increase in the relative trading volume as well as the decreases in the daily expected stock return and firm level volatility in the post-Sina Weibo period. These findings suggested that Sina Weibo as an alternative information interaction channel has changed the information environment for individual stock, enhanced the speed of information diffusion and therefore changed the overall stock market behavior.

Lovejoy, K., *et al.*, [12] examined how 73 nonprofit organizations use Twitter to engage stakeholders not only through their tweets, but also through other various communication methods. Specifically, it looks into the organizations' utilization of tweet frequency, following behavior, hyperlinks, hashtags, public messages, retweets, and multimedia files.140 characters seems like too small a space for any meaningful information to be exchanged, but Twitter users have found creative ways to get the most out of each Tweet by using different communication tools. After analyzing 4,655 tweets, the study found that the nation's largest nonprofits are not using Twitter to maximize stakeholder involvement. Instead, they continue to use social media as a one-way communication channel, as less than 20% of their total tweets demonstrate conversations and roughly 16% demonstrate indirect connections to specific users. However, smaller, community-based nonprofits were excluded from the research in favor of large, national nonprofits. It can be argued that smaller, grassroots nonprofits may be more interactive and use conversational tweets with their followers rather than using one-way information dissemination practices

Schumaker, R.P., *et al.*, [13] examined the Central Sport system to gather tweets related to the twenty clubs of the English Premier League and analyze their sentiment content, not only to predict match outcomes, but also to use as a wagering decision system. This result may suggest a performance degradation that arises from conservatism in the odds-setting process, especially when three match results are possible outcomes. The leveraging a positive tweet sentiment surge over club average could net a payout of $3011.20. Lastly, the magnitude of positive sentiment between two clubs increased was found, so too did the point spread; 0.42 goal difference for clubs with a slight positive edge versus 0.90 goal difference for an overwhelming difference in positive sentiment. In both these cases, the cultural expectancy of positive tweet dominance within the twitter-base may be realistic. These outcomes may suggest that professional odds-making excessively predicts non-positive match outcomes and tighter goal spreads. These results demonstrate the power of hidden information contained within tweet sentiment and has predictive implications on the design of automated wagering systems. However, only one hashtag per club may be limited compared to gathering an entire universe of club-related tweets, the volume of tweets gathered offsets the limitation.

Zhang, X., *et al.*, [14] examined user domain knowledge can be predicted from search behaviors by applying a regression modeling analysis method. The behavioral features that contribute most to a successful prediction model were identified. A user experiment was conducted with 40 participants searching on task topics in the domain of genomics. Participant domain knowledge level was assessed based on the users' familiarity with and expertise in the search topics and their knowledge of MeSH (Medical Subject Headings) terms in the categories that corresponded to the search topics. Users' search behaviors were captured by logging software, which includes querying behaviors,

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document selection behaviors, and general task interaction behaviors. The models were compared for the best on model fit, significance of the model, and contributions of individual predictors in each model. Each model was validated using the split sampling method. The final model highlights three behavioral variables as domain knowledge level predictors. However, controlled experiment provided the user data, such control is gained at the cost of generalizability. The selected subject field, the specially implemented experimental search system, and well-defined database that the participants could access are limitations to generalizability.

Flöter, T. *et al.*, [15] considered mega event sponsorship which is an increasingly challenging, sponsors often link their sponsorship to corporate social responsibility (CSR) activities. However, finding adequate ways to communicate CSR linked sponsorship is challenging. This research examines the relative effectiveness of three message sources from which CSR-linked sponsorship information can be communicated to consumers: the sponsor, the sponsored property, and the news media. Drawing on the Persuasion Knowledge Model, this study developed differences between these message sources regarding their level of persuasion knowledge activation, which affects consumers' CSR perceptions of and attitude toward the sponsoring brand. The results of an experimental study show that CSR-linked sponsorship information from both the sponsor and the sponsored property result in higher persuasion knowledge activation than when this information comes from the news media. The results also reveal that the two serial mediators, persuasion knowledge activation and CSR perception, transfer these effects of message source to consumers' attitudes toward the sponsor. However, the small sample size which reduced statistical power. This limitation offers another potential explanation for the failure to provide full support for the first hypothesis that complements the conceptual arguments presented above

The limitations developed in the developed existing methods were considered and an efficient proposed model is developed that gives better results compared with the existing techniques.

III. PROPOSED METHOD

In this paper our main motivation is to analyze the tweets related to Cricket matches (ICC World Cup-2015) to analysis the impact of sponsor stocks. We have collected tweets by using the twitter streaming. The block diagram of the proposed methodology is shown in the figure 3.1

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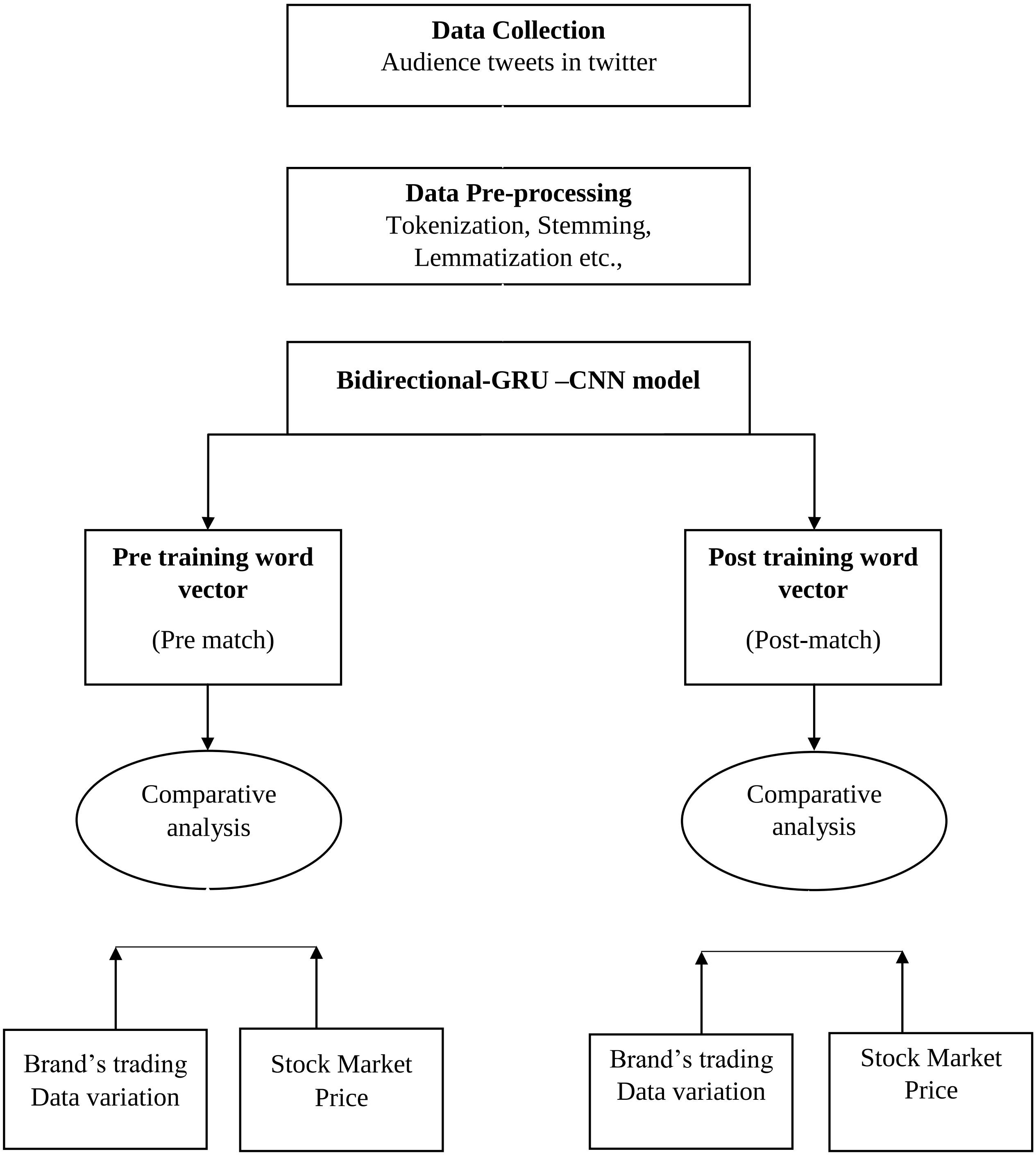

Figure 3.1: An Overview of the proposed methodology

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3.1 Data collection

The data are collected from the twitter related to Cricket matches (ICC World cup 2015). The collected tweets by using the twitter streaming. Tweets can be extracted in two ways either by using hashtags or by location. We have extracted tweets with CWC'15-related hashtags such as #cwc15, #cwc2015, #iccworld-cup2015, #worldcup2015 etc. from Feb 13, 2015 to Mar 30, 2015 [16]. We considered the hashtags and keywords related to each match to investigate the volume of match specific Twitter discussion. The dataset consists of pre-match and post-match tweets for every match played by India. Statistics of match wise (pre & post) tweets counts are shown in table 3.1. Some of the players have very less number of pre & post tweets which implies either the player did not get chance to bat or their performance were not up to the mark. It is an open source web facility that determines search frequency for a particular term. The search frequency is determined relative to the total search volume across different regions of the world.

Table 3.1: Match wise Tweets statistics

Date	India vs Opponent	Number of Tweets
14 February 2015	India vs Pakistan	40,12,423
22 February 2015	India vs South Africa	10,08,273
19 March 2015	India vs Bangladesh	2,90,865
26 March 2015	India vs Australia	5,95,864

The data are categorized based on the following criteria,

- **Match wise Tweets selection:** The streaming tweets are collected by using appropriate hashtags are that handles particular match. A time window is decided for pre and post-match tweets acquisition. As Tweets frequency increases when time approaches to match start time and frequency decreases down the line with time after completion. Therefore, to have the full coverage of tweets, minimum time window is taken as 4 hours for pre and post-match session.
- **Brand identification and date specific collection of trading data:** Key sponsors for the team are identified, along with this each player is tagged with a brand what he endorses. All the tagged brands are taken in account and their trading performances are acquired during the commencement of match.
- **Player specific popularity extraction:** The popularity of a player can directly be decided with number of queries fired pertaining that person on Internet through the twitter. The achievements of a person on global state lead others to know about the person and its work. Popularity is a volatile property of an individual which is triggered by gets fade with time. Bringing the same concept to the context of the players the popularity of each player is extracted with the help of Google Trends such as tweets from the twitter site.

The data accumulated from the data collection step need to be processed for preprocessing in order to extract the efficient words and filter certain unnecessary categories of words. This is functioned by data pre-processing which is explained in the next section.

3.2 Data Pre-processing

Transforming text into something an algorithm can digest is a complicated process. In this section, the steps involved in text processing are as follows [17].

(i) Tokenization: Tokenization includes conversion of sentences to words also called as tokens before transforming it into vectors. The unnecessary tokens are easy to filter, where a document is transformed into paragraphs or sentences into words. In our research work, the online reviews are tokenizing into words.

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(ii) Removal of Unnecessary tags and Punctuation: The next step is to remove punctuation, as the punctuation doesn't do any extra information while treating text data. Therefore, removing all instances will help to reduce the size of the training data.
(iii) Removing stop words: Frequent words such as "the", "is", etc. that do not have specific semantic. The search engine has been programmed to ignore, both when indexing entries for searching and when retrieving them as the result of a search query. Those words that appear sparsely in the appraisal relationship will be filtered out. The list of words that are not to be added is called a stop list.
(iv) Stemming: The words are reduced to a root by removing inflection through dropping unnecessary characters, usually a suffix. Stemming is the process of reducing a word to its word stem that affixes to suffixes and prefixes or to the roots of words known as a lemma. Stemming is important in an efficient Natural Language Understanding and Natural Language Processing to get the actual context of the words.
(v) Lemmatization: Another approach to remove inflection by determining the part of speech and utilizing detailed database of the language. Thus stemming & lemmatization help to reduce a common base form or root word.
For the prediction of stock market price, we are going to consider the textual parts for analyzing the sentiment expressed by the audience. The deep explanation is given in the next section.

3.3 Bidirectional Gated Recurrent Unit - Convolutional Neural Network model

In this section, a deep neural model for the prediction of stock market price that obtains for the sponsors if the sportsman is considered as an ambassador for promoting company's brand. The block diagram of the proposed model is shown in the figure 3.2. As an input, the network receives a job description post, which includes title, contents, requirements, working time, job location, and job type and salary. The output of the front network contains context elements [18].

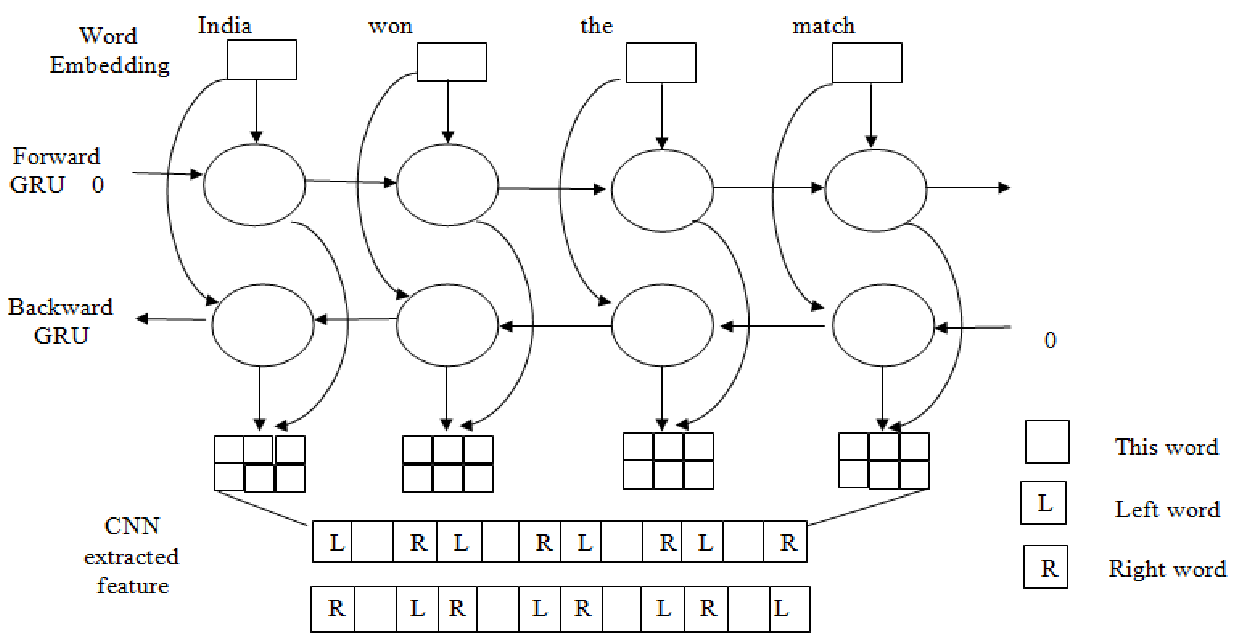

Figure 3.2: Block diagram of Bidirectional Gated Recurrent Unit - Convolutional Neural Network

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3.3.1 Gated Recurrent Unit Recurrent Neural Network

Gated Recurrent Unit Recurrent Neural Network is widely used in NLP field, which can learn context information of one word. Long Short Term Memory is designed to solve RNN gradient vanishing problem, especially in learning long sentence Gated Recurrent Unit (GRU) is a simplified LSTM cell structure. Taking advantage of its simple cell, GRU can get a close performance to LSTM with less time. Likewise, Bidirectional Gated Recurrent Unit - Convolutional Neural Network (Bi-GRU-CNN) exhibits strength in feature representation, context feature and cannot be incorporated very well by multi-size kernels [19]. To combine a word and its context together, we first process words using a Bi-GRU-CNN in the following way. One word in a sentence can be learn from forward and backward twice in bidirectional structure, which can get more word representation features and avoid some gradient vanishing problem in long sentence. For comparing performance of RNN, LSTM and GRU, we design in a series of models in our work.

The Text CNN apply multi-channel and different kernel size one dimensional convolutional structure on text data classification. In this work, considering our data particularity. Different from semantic representation on classification task, some keyword representation is more important on job information regression. After Bi-GRU-CNN learning context information, multi-channel convolutional layer can learn better features than Text CNN. After concatenate multi-channel CNN output, we use a fully connection layer to finish regression work. Between each of the dense layer, we add dropout and batch normalization layer to avoid gradient vanishing. Pre-training word vectors Pre-training word level vector already is a basic part in deep learning model for prediction of the hopes percentage given by the audience before the match begins (pre-match). Similarly, Post- training word vectors are utilized for the prediction of the stock market price that is mainly dependent on the performance of the players in the match after the match (post-match) [20]. The Bi-GRU-CNN model will also handle scenarios like,

- Player's name as hash tags, their handles such as imvkohli, imvkohli, Virat are taken for clubbing the new Tweets.
- Emotion Extractions and Knowledge Discovery are used National Research Council (NRC) Emotion Lexicon for extracting emotions from Twitter data. NRC Emotion Lexicon consists of words and their association with 8 emotional classes (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive). All the player wise clustered tweets are segregated between pre match and post-match tweets. All the tweets are tokenized to produces a bag-of-words. Each of the words are plugged-in for emotion and sentiment classification and so pre match and post-match emotional score is attained for each player.

$$r(X,Y) = \frac{N\sum XY - (\sum X \sum Y)}{\sqrt{[N\sum x^2 - (\sum x)^2][N\sum y^2 - (\sum y)^2]}} \quad (1)$$

This function finds the availability of category wise emotion index in each of the words and keeps increasing the score as new words are encountered. Score is the vector of 10 in which each index represents particular emotion or sentiment. Score Vector Score is calculated for all the words in tweet dataset. Correlation score represented by S is the extracted knowledge as an output of the given algorithm. Tabulation of distinct sportsman's fan base tweets comprised of the emotions as well as the tweets obtained for Pre match (before the match) and Post-match (after the match) is shown in table 3.2.

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Table 3.2: Tabulation of distinct sportsman's fan base tweets comprised of the emotions as well as the tweets obtained for Pre match (before the match) and Post-match (after the match)

Name	Tweets	Emotion	India vs. Pakistan	Emotion	India vs. South Africa	Emotion	India vs. Bangladesh	Emotion	India vs. Australia
Shikhar Dhawan	Pre Post	Fear Joy	15635 17535	Fear Joy	16372 8943	Anticipate Joy	18423 19547	Trust Joy	15635 17535
MS Dhoni	Pre Post	Trust Joy	17535 10457	Joy Joy	20132 21732	Anticipate Joy	1789 1943	Trust Joy	17535 10457
Ravindra Jadeja	Pre Post	Fear Joy	15746 16743	Anticipate Joy	2242 4524	Fear Joy	1704 6053	Sad Joy	15746 16743
Virat Kohli	Pre Post	Trust Joy	17423 10547	Joy Trust	20353 20342	Joy Trust	12753 19532	Fear Joy	17423 10547
Bhuvneshwar Kumar	Pre Post	Fear Surprise	1789 1943	Joy Trust	1735 3943	Sad Trust	14428 16635	Joy Anticipate	11789 11943
Ajinkya Rahane	Pre Post	Anticipate Joy	1904 1053	Joy Fear	3675 4830	Fear Trust	1554 1663	Joy Trust	11904 11053
Suresh Raina	Pre Post	Fear Sad	12753 13532	Fear Anger	17464 16483	Joy Fear	19748 18773	Fear Joy	12753 13532
Rohit Sharma	Pre Post	Fear Joy	14426 16636	Fear Trust	16324 17873	Trust Fear	1753 1673	Surprise joy	14426 16636
Mohammed Shami	Pre Post	Fear Anticipate	1579 1647	Fear Joy	762 909	Anticipate Joy	15,748 18,573	Fear Joy	1579 1647
Ravichandran Ashwin	Pre Post	Joy Fear	15,748 18,573	Sad Joy	16,438 18,432	Disgust Joy	1753 1673	Surprise joy	15,748 18,573
Stuart Binny	Pre Post	Anticipate Joy	1753 1673	Sad Joy	1234 2863	Anticipate Fear	16,438 18,432	Surprise Trust	1753 1673

The rows in the table 3.2 represent the values of pre and post-match emotions respectively. The key players like Virat Kohli, Rohit Sharma, MS Dhoni captured the largest part of Tweets[21]and so the emotions. As Raina performed lower and could not perform up to the mark of fans therefore sadness emotions gets increased in every match played by him. As MS Dhoni performed as a dark horse in the Bangladesh match, so he could reinforce all the positive emotions Trust, joy among his fans and could succeed to suppress negative emotions like Fear, Anger, Disguest. Few emotions are found very consistent throughout the matches and are noticed as facing the direct impact of whether team has won or lost.

IV. RESULTS AND DISCUSSION

The proposed architecture extracts emotions and sentiments from a cricket loving country and shows how do emotions affect stock market's performance of various commercial brands whose brand ambassadors actively

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participate in the game. The study reveals that performance of the brand ambassador has direct impact on the brand's price on stock exchange. All 4 cricket matches of an ICC event (ICC Cricket World Cup 2015) played by their team against 'Pakistan', 'South Africa', 'Bangladesh and final again with 'Pakistan' are taken under consideration for analysis. The results show how the fans' emotions change as the game commences. Because of uneven counting of emotions for each player in particular emotional category, in this work all the emotions are scaled down between 0 to 1 with respect to total number of emotions, corresponding to each player. The figure 4.1 and figure 4.2 shows the variance of particular emotion with matches and popularity of the players can be seen through twitter trends over the globe for batsmen and bowlers.

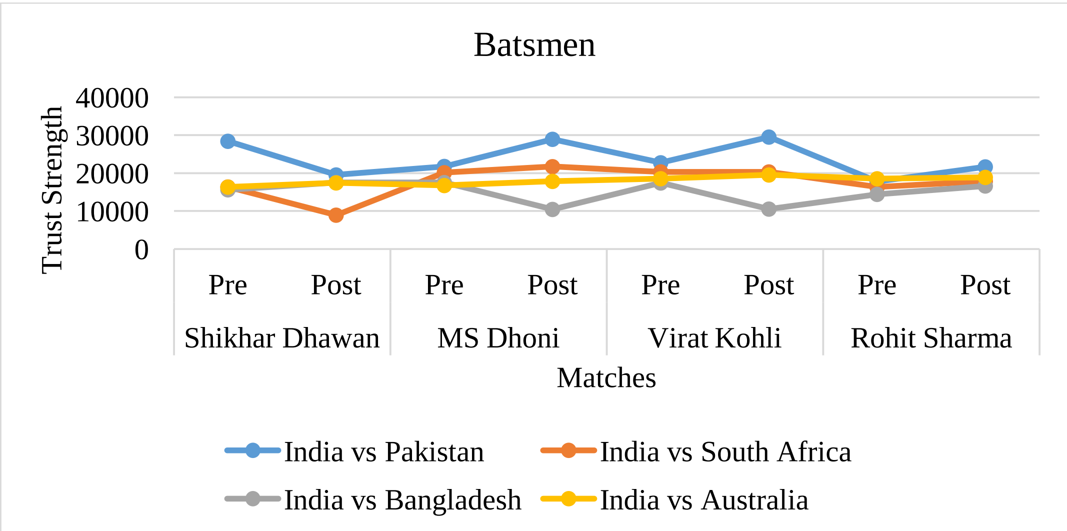

Figure 4.1: Graph representation of Batsmen popularity obtained in the tweets accordingly to the scheduled matches

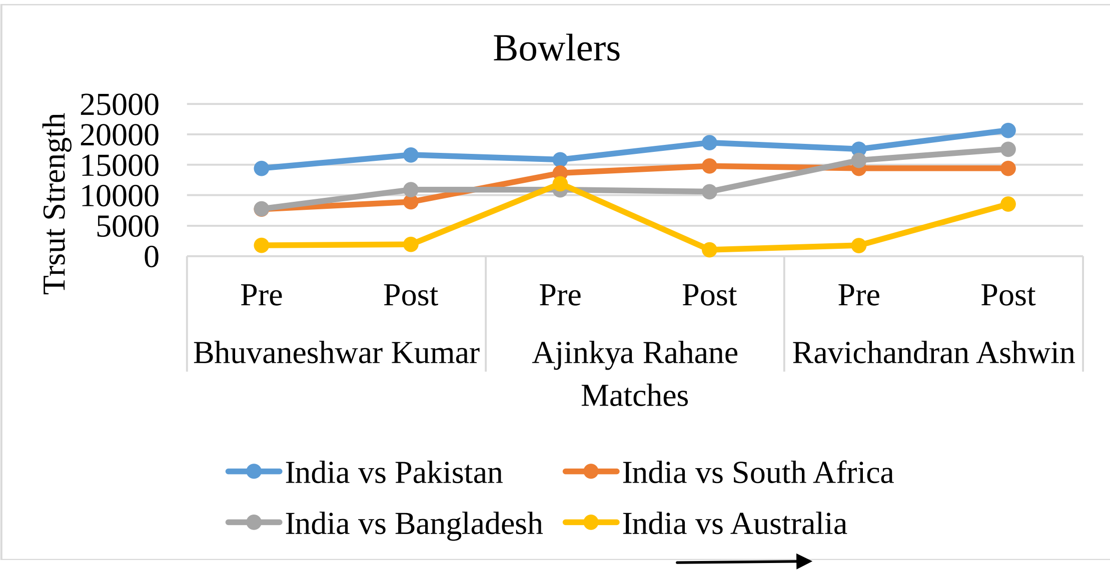

Figure 4.2: Graph representation of Bowlers popularity obtained in the tweets accordingly to the scheduled matches

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Table 4.1: Tabulation of distinct brands stock market price in comparison with the matches played for different countries

Player	Brand [22]	Tweet	Stock market data for India vs Pakistan	Stock market data for India vs Bangladesh	Stock market data for India vs Australia
Virat Kholi	Boost (Energy drink)	Pre Post	4352.65 4524.53	1284.91 3343.5	1277 3524.9
MS Dhoni	Snickers	Pre Post	4502.85 4789.9	1253.39 2464.4	1260.8 3673.6
Rohit Sharma	Adidas	Pre Post	4515.15 5876.23	1203.43 1260.31	1236.68 3673.57

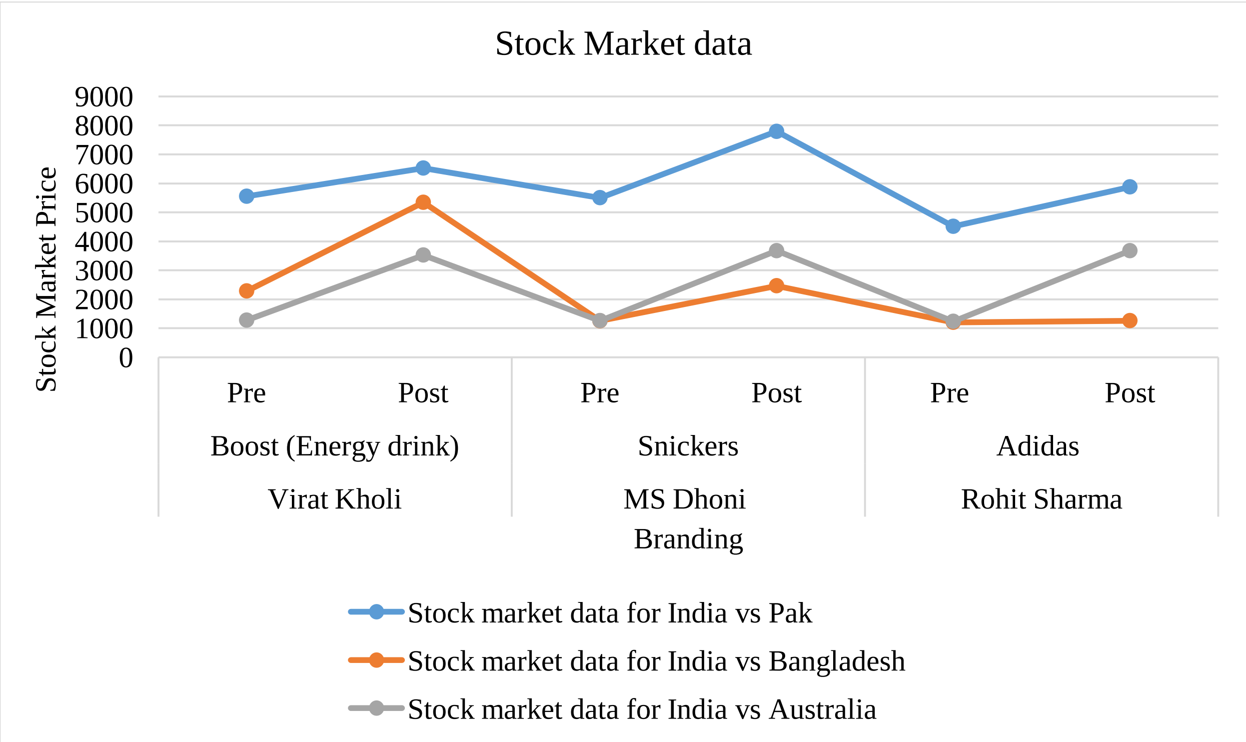

Figure 4.3: Graphical representation of distinct brands stock market price in comparison with the matches played for different countries.

We observed that changes in emotions between pre and post-match sessions were positive when that individual player performed well and negative otherwise. Along with these emotions we have collected sentiments through pre match session tweets and post-match session tweets with binary values as positive or negative. It is observed that even if player could not perform well but if team wins, sentiments are noted as positive. This shows that sentiments are more consistent with the Team than with the player. Trading price of commercial brands are found to have transitive relationship with their brand ambassador's performance in the match as shown in table 4.1. The Table 4.1 and figure 4.3 shows a comparison graph between distinct players receiving the tweets obtained for their performances in the different matches. Good performance spreads happiness among fans that gives jump in trading price and bad performance discourages the fans and their commercial activities so their average mood leads to fall in stock prices is

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shown in table 4.1 and the comparison graph for the 3 players with respect to their brands is shown in variation in the stock price values before and after the match in the figure 4.3.

V. CONCLUSION

The experimental setup utilized tweets pertaining Indian team throughout the ICC World cup tournament 2015. For all the matches we have extracted emotions/sentiments 8 classes (Joy, Fear, Anger, Anticipation, Trust, Sadness, Surprise, and Disgust) before and after the match. We have established one to one correspondence between players' performance and fan's emotions for that player and this study uses total 8 categories of emotions and 2 sentiments for this purpose. This work picks few key players of the team on performance basis and finds their commercial endorsements. Next, we analyzed the impact of their performance on the emotions of the twitter followers as well as on the stock prices of the brands which they are endorsing. In our observations we have noticed high correlation of player's performance with corresponding emotions/ sentiments as well as on stock prices of the brand they endorsed. In the present work, we have extracted pre-match & post-match emotions and acquired the trading data of corresponding date. After that we have calculated the correlation between variations in emotions and trading data. However, the future work should be designed regarding the prediction of the results of the match as win or loss and the impact of stock market price on results

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