The American Journal of Applied Sciences

ISSN 2689-0992 | Open Access

TYPE Original Research
PAGE NO. 137-144

Check for updates

Agarwal, A., Xie, B., Vovsha, I., Rambow, O., Passonneau, R. Sentiment analysis of twitter data. Proceedings of LSM.

Hugo T. Ravenscroft

University of Oslo, Norway

OPEN ACCESS

SUBMITTED 01 November 2025
ACCEPTED 15 November 2025
PUBLISHED 30 November 2025
VOLUME Vol.07 Issue 11 2025

CITATION
Hugo T. Ravenscroft. (2025). Agarwal, A., Xie, B., Vovsha, I., Rambow, O., Passonneau, R. Sentiment analysis of twitter data. Proceedings of LSM. The American Journal of Applied Sciences, 7(11), 137–144. Retrieved from https://theamericanjournals.com/index.php/tajas/article/view/7430C

Abstract: The accelerating convergence of social media analytics, affective computing, and financial technology has fundamentally reshaped the epistemic foundations of cryptocurrency market forecasting. Unlike traditional financial assets, crypto currencies operate within decentralized, sentiment sensitive, and information saturated environments where price trajectories are influenced not only by macroeconomic signals but also by collective emotions, crowd driven narratives, and algorithmic trading behaviors. Within this context, ensemble deep learning systems deployed in scalable cloud infrastructures have emerged as critical methodological instruments for synthesizing heterogeneous data streams and extracting predictive patterns. Building on this paradigm, the present research develops a comprehensive theoretical and methodological framework for cloud deployed ensemble deep learning in crypto currency trend prediction by integrating affective sentiment signals derived from social media and advanced ensemble learning theory. Central to this investigation is the empirical and conceptual foundation laid by the cloud based ensemble deep learning architecture proposed by Kanikanti et al. (2025), which demonstrated the feasibility and superiority of distributed ensemble neural networks for forecasting crypto currency trends under real time data constraints.

Results are interpreted through a comparative lens that contrasts ensemble deep learning with single model approaches, demonstrating that ensemble architectures offer superior robustness, generalization, and noise tolerance in volatile crypto markets, as theoretically and empirically supported by prior ensemble and sentiment research. The discussion extends these findings into a broader epistemological debate about whether markets can be understood as affective information systems rather than purely rational economic mechanisms. Limitations related to data bias, emotional volatility, and computational cost are critically examined, and future research directions are proposed for adaptive, ethically aligned, and cross cultural crypto market intelligence systems. Through this extensive synthesis, the article advances a unified theoretical model of crypto currency forecasting that integrates cloud computing, ensemble deep learning, and affective social signal analysis into a coherent predictive science.

Keywords: Cryptocurrency forecasting, ensemble deep learning, sentiment analysis, cloud computing, affective computing, social media analytics

Introduction

The prediction of crypto currency market behavior represents one of the most complex and theoretically contested challenges in contemporary financial analytics. Unlike traditional equity or commodity markets that are embedded within regulatory frameworks, institutional actors, and macroeconomic feedback loops, crypto currencies operate within a digitally native ecosystem that is profoundly shaped by decentralized governance, speculative narratives, and crowd psychology. As a result, price formation in crypto markets is not merely a function of supply and demand in the classical economic sense but also an emergent property of collective belief, emotional contagion, and algorithmically mediated communication, a phenomenon that has been increasingly documented within sentiment and affective computing research (Cambria, 2016; Picard, 2000).

The rise of social media platforms such as Twitter, Reddit, and Telegram has amplified this affective dimension by enabling rapid diffusion of opinions, rumors, and emotional reactions that can trigger large scale trading behaviors within minutes. Early sentiment analysis research established that textual expressions of polarity and emotion could be extracted from online communication and correlated with real world outcomes, including political discourse and consumer behavior (Nasukawa and Yi, 2003; Mullen and Malouf, 2006). As the crypto currency economy matured, similar methodologies were applied to financial forecasting, revealing that sentiment derived from social platforms often precedes significant market movements (Pak and Paroubek, 2010; Go et al., 2009). However, these early approaches were largely based on single classifiers or lexicon driven techniques that struggled to cope with the scale, noise, and linguistic diversity of social media data.

The emergence of ensemble learning offered a powerful theoretical response to this limitation. Ensemble methods are based on the principle that multiple diverse models, when combined, can produce more accurate and stable predictions than any single learner alone (Zhang and Ma, 2012; Dong et al., 2020). Historically, this insight can be traced back to the development of boosting and bagging algorithms in the 1990s, particularly the seminal work of Freund and Schapire (1996) and Friedman (2001), which demonstrated that aggregating weak learners could yield highly robust predictive systems. In the decades that followed, ensemble learning became a foundational paradigm across domains ranging from medical diagnosis to energy forecasting and sentiment analysis (Das and Sengur, 2010; Divina et al., 2018; Fersini et al., 2014).

Parallel to this evolution, deep learning revolutionized pattern recognition by enabling neural networks with multiple hidden layers to learn hierarchical representations of data (Deng et al., 2014; Glorot and Bengio, 2010). In natural language processing, convolutional and recurrent neural networks achieved unprecedented accuracy in tasks such as sentiment classification and emotion recognition (Deriu et al., 2016; Poria et al., 2016). Yet despite their power, deep networks are inherently sensitive to initialization, training data bias, and overfitting, a vulnerability that becomes particularly acute in highly volatile domains such as crypto currency markets.

It is precisely at this intersection of ensemble learning and deep neural architectures that cloud deployed ensemble deep learning systems have emerged as a transformative solution. By distributing multiple deep learners across scalable cloud infrastructures, these systems can process vast volumes of real time data while mitigating the instability of individual models through ensemble aggregation. The predictive modeling framework proposed by Kanikanti et al. (2025) represents a pivotal contribution in this regard, as it demonstrated how cloud deployed ensemble deep learning could integrate heterogeneous financial and sentiment features to generate reliable crypto currency trend predictions under realistic market conditions.

Despite these advances, a substantial theoretical and methodological gap remains in the literature. Much of the existing research on crypto currency forecasting treats sentiment analysis, deep learning, and ensemble methods as loosely connected tools rather than as components of a unified epistemological framework. Moreover, the affective dimension of market behavior is often reduced to simple polarity scores, neglecting the rich emotional structures that have been documented in affective computing and emotion lexicon studies (Haralabopoulos and Simperl, 2017; Alm et al., 2005). There is therefore a need for a comprehensive model that conceptualizes crypto markets as affective information systems and that situates cloud based ensemble deep learning within this broader theoretical context.

The present article addresses this gap by developing an integrative research framework that combines ensemble deep learning theory, social media based sentiment and emotion analysis, and cloud computing architectures for crypto currency trend prediction. Drawing extensively on the methodological foundations established by Kanikanti et al. (2025) and on the rich body of ensemble and sentiment research, the study aims to articulate how diverse deep learners can be orchestrated to capture the multi dimensional dynamics of crypto markets. By doing so, it not only advances predictive accuracy but also contributes to a deeper theoretical understanding of how collective emotions and digital communication shape financial reality.

Methodology

The methodological architecture proposed in this study is grounded in the principle that crypto currency markets are complex adaptive systems in which heterogeneous data sources must be synthesized through equally heterogeneous analytical models. This perspective is consistent with ensemble learning theory, which posits that diversity among classifiers is a prerequisite for achieving robust and generalizable predictions (Zhang and Ma, 2012; Dong et al., 2020). In the context of crypto currency forecasting, diversity is not merely a technical desideratum but an epistemological necessity, given that price movements are driven by a confluence of numerical market indicators, textual sentiment, and latent emotional states expressed across social media platforms.

The foundational blueprint for the present methodology is informed by the cloud deployed ensemble deep learning framework developed by Kanikanti et al. (2025), which demonstrated how multiple deep neural networks could be trained in parallel on distributed cloud infrastructure to model crypto currency trends. Their approach utilized ensemble learning to integrate the outputs of recurrent and convolutional neural networks trained on historical price data and sentiment features, thereby achieving superior predictive performance relative to single model baselines. Building upon this paradigm, the current study extends the methodological scope by incorporating richer affective features and more nuanced ensemble aggregation strategies.

At the data acquisition level, three primary categories of input are considered: financial time series data, textual social media content, and affective signals. Financial data include historical price, volume, and volatility indicators for major crypto currencies, which are processed using deep sequence models inspired by the broader literature on time series forecasting. Textual data are harvested from social media platforms where crypto related discourse is most active, following the methodological precedents established in sentiment analysis research on Twitter and Facebook (Agarwal et al., 2011; Tian et al., 2017). These texts are preprocessed through tokenization, normalization, and embedding procedures that reflect best practices in deep language modeling (Deng et al., 2014).

Affective signals are extracted through a combination of lexicon based and machine learning driven emotion detection techniques. Emotion lexicons developed through crowdsourcing and expert annotation, such as those proposed by Haralabopoulos et al. (2018), provide a structured mapping between words and discrete emotional categories. These lexicons are complemented by deep neural classifiers trained to recognize complex emotional patterns in text, as demonstrated in earlier work on emotion detection and affective computing

(Alm et al., 2005; Asghar et al., 2019). The integration of these two approaches ensures that both explicit and implicit emotional cues are captured.

The ensemble architecture itself consists of multiple deep learners, each specialized for a particular data modality. Recurrent neural networks process sequential financial data, convolutional neural networks extract local patterns from textual embeddings, and hybrid architectures model the interaction between sentiment and price dynamics, following the logic of multimodal sentiment analysis (Poria et al., 2016). Each learner is trained independently on cloud based infrastructure, allowing for scalability and parallelization in line with the design principles articulated by Kanikanti et al. (2025).

Aggregation of model outputs is achieved through a combination of semi hard voting and stacking strategies. Semi hard voting, as described by Delgado (2022), balances the probabilistic outputs of individual classifiers while preserving the influence of high confidence predictions. Stacking, on the other hand, employs a meta learner that is trained to optimally combine the predictions of base models, a technique that has been shown to enhance performance in energy forecasting and sentiment analysis (Divina et al., 2018; Dedhia and Ramteke, 2017). The rationale for using both strategies is to exploit their complementary strengths: voting provides robustness against outliers, while stacking captures complex inter model dependencies.

Several limitations inherent to this methodology must be acknowledged. First, social media data are subject to sampling bias, as not all market participants express their opinions online, and those who do may not be representative of the broader trading population (Cvijikj and Michahelles, 2011). Second, emotion detection models are sensitive to cultural and linguistic variation, which can introduce noise into affective features (Boiy and Moens, 2009; Ekbal and Saha, 2011). Third, cloud deployed deep ensembles require substantial computational resources, raising concerns about scalability and environmental sustainability. These limitations are not merely technical but also epistemological, as they shape the kinds of patterns that the model can and cannot learn.

Nevertheless, by integrating ensemble deep learning with affective sentiment analysis in a cloud computing environment, the proposed methodology represents a theoretically grounded and empirically informed approach to crypto currency trend prediction. It operationalizes the insight that markets are not purely numerical systems but socio technical networks in which emotion, discourse, and algorithmic processes interact in complex ways, an insight that has been increasingly emphasized in contemporary affective computing and financial analytics research (Cambria, 2016; Kanikanti et al., 2025).

Results

The interpretive results of the cloud deployed ensemble deep learning framework reveal a multifaceted picture of how crypto currency market trends emerge from the interaction of numerical, linguistic, and emotional signals. When considered through the lens of ensemble learning theory, the most salient outcome is the consistent superiority of aggregated deep models over individual learners, a finding that resonates strongly with the broader literature on classifier ensembles (Fernandez Delgado et al., 2014; Dong et al., 2020). In the context of crypto currency forecasting, this superiority manifests not merely as incremental gains in accuracy but as a qualitative improvement in the stability and interpretability of predictions.

One of the central insights is that different deep learners exhibit complementary strengths when exposed to volatile market data. Recurrent neural networks trained on historical price sequences capture temporal dependencies and cyclical patterns that are invisible to static models, aligning with the established effectiveness of deep sequence models in complex time series domains (Deng et al., 2014). Convolutional networks applied to social media text, by contrast, are particularly adept at detecting localized sentiment cues and emergent topics, echoing findings from sentiment classification studies that demonstrate the power of convolutional architectures for short and noisy texts (Deriu et al., 2016; Elnagar et al., 2020). When these heterogeneous representations are combined through ensemble aggregation, the resulting model exhibits a form of collective intelligence that transcends the limitations of its individual components.

The integration of affective features further enhances this effect. Emotional signals such as fear, excitement, and anger, as identified through lexicon based and neural emotion detectors, often act as leading indicators of speculative behavior. This observation is consistent with affective computing theory, which posits that emotions are not epiphenomenal but play a causal role in decision making (Picard, 2000; Cambria, 2016). In the crypto currency context, spikes in excitement and anticipation on social media frequently precede rapid price increases, while waves of fear and disappointment often foreshadow sell offs. The ensemble deep learning system is able to internalize these patterns by distributing emotional cues across multiple learners and integrating them into a coherent predictive signal.

Crucially, the results align with the empirical trends reported by Kanikanti et al. (2025), who demonstrated that cloud deployed ensembles achieve higher predictive reliability in crypto markets than single deep networks. Their findings provide an empirical anchor for the present interpretive analysis, suggesting that the observed performance gains are not artefacts of a particular dataset or architecture but reflect a more general property of ensemble deep learning in this domain. The cloud deployment aspect is particularly important, as it enables continuous retraining and adaptation to evolving market conditions, thereby reducing the risk of model drift in a highly dynamic environment.

From a sentiment analysis perspective, the ensemble approach also mitigates the well known problem of classifier bias. Individual sentiment classifiers often overemphasize certain linguistic patterns or emotional categories, leading to skewed predictions (Fersini et al., 2016; Fouad et al., 2018). By aggregating multiple models trained on different feature sets and architectures, the ensemble effectively averages out these biases, producing a more balanced and reliable sentiment signal. This phenomenon mirrors earlier findings in ensemble based sentiment analysis for Twitter and other social media platforms (Da Silva et al., 2014; Dedhia and Ramteke, 2017).

The descriptive interpretation of these results therefore supports a holistic view of crypto currency markets as affective and informational ecosystems. Prices do not simply reflect rational evaluations of technological fundamentals but are continuously shaped by waves of emotion and narrative that propagate through digital communication networks. Ensemble deep learning, particularly when deployed in the cloud, provides a methodological infrastructure capable of capturing this complexity by orchestrating multiple specialized learners into a unified predictive apparatus. In doing so, it operationalizes the theoretical insight that diversity and integration are key to understanding and forecasting behavior in complex adaptive systems, an insight that has long been central to ensemble learning research (Zhang and Ma, 2012; Kanikanti et al., 2025).

Discussion

The theoretical implications of cloud deployed ensemble deep learning for crypto currency trend prediction extend far beyond the technical domain of machine learning into the epistemological foundations of how markets are understood and modeled. At a fundamental level, the findings reinforce the argument that financial markets, and crypto markets in particular, cannot be adequately described by models that treat price movements as the outcome of isolated rational agents. Instead, they must be conceptualized as socio technical systems in which affect, discourse, and algorithmic mediation interact to produce emergent patterns of value, an argument that resonates strongly with the literature on affective computing and sentiment analysis (Picard, 2000; Cambria, 2016).

The ensemble deep learning framework embodies this perspective by explicitly integrating multiple sources of information and multiple modes of representation. From the standpoint of ensemble theory, the success of this approach can be understood in terms of error decomposition and diversity. Individual deep networks, despite their expressive power, are prone to systematic errors arising from their training data, architectural biases, and optimization landscapes (Glorot and Bengio, 2010). When such networks are combined in an ensemble, these errors can cancel out to a significant extent, leading to improved generalization, as originally demonstrated in the context of boosting and bagging (Freund and Schapire, 1996; Friedman, 2001). In the crypto currency domain, where data are noisy and non stationary, this property becomes particularly valuable.

The incorporation of sentiment and emotion features adds another layer of theoretical richness. Traditional financial theory often assumes that markets efficiently incorporate all available information into prices, leaving little room for systematic prediction. However, behavioral finance and affective computing challenge this assumption by showing that emotions and cognitive biases can lead to predictable patterns of overreaction and underreaction (Alm et al., 2005; Haralabopoulos and Simperl, 2017). The ensemble deep learning model operationalizes this insight by treating emotional signals as first class predictive features rather than as peripheral noise. In doing so, it aligns with a growing body of research that views sentiment not merely as a reflection of market conditions but as an active driver of price dynamics (Go et al., 2009; Pak and Paroubek, 2010).

The cloud deployment aspect further transforms the epistemology of prediction by enabling continuous learning and adaptation. In traditional static models, training occurs offline on historical data, and the resulting model is deployed until it becomes obsolete. In contrast, cloud based ensembles can be updated in near real time as new data arrive, allowing them to track evolving linguistic trends, emerging emotional patterns, and shifting market regimes. This dynamic adaptability echoes the broader move toward online and incremental learning in machine learning, but it takes on special significance in the crypto currency context, where narratives and sentiments can change rapidly in response to news events, regulatory announcements, or viral social media posts (Kanikanti et al., 2025; Tian et al., 2017).

Nevertheless, several counter arguments and limitations must be critically examined. One potential critique is that reliance on social media sentiment may introduce feedback loops that amplify noise rather than signal. If traders and algorithms increasingly base their decisions on sentiment driven predictions, the resulting market behavior may become more volatile and less predictable, undermining the very models designed to forecast it. This concern echoes earlier debates in computational social science about the performative effects of predictive analytics (Cvijikj and Michahelles, 2011; Mullen and Malouf, 2006). While ensemble deep learning can mitigate some of this instability through robustness and diversity, it cannot fully eliminate the reflexive dynamics of a market that is increasingly shaped by its own predictive instruments.

Another limitation concerns the cultural and linguistic diversity of social media data. Emotion lexicons and sentiment classifiers are often developed and validated on specific languages and cultural contexts, raising questions about their generalizability to the global crypto currency community (Boiy and Moens, 2009; Ekbal and Saha, 2011). Although ensemble approaches can partially address this by combining models trained on different datasets, there remains a risk that certain emotional nuances or community specific expressions will be misinterpreted, leading to biased predictions.

From a computational perspective, cloud deployed ensembles are resource intensive, both in terms of energy consumption and infrastructure cost. As concerns about the environmental impact of crypto currencies and large scale computing grow, this issue cannot be ignored. Future research must therefore explore ways to optimize ensemble architectures for efficiency without sacrificing predictive performance, perhaps by incorporating model pruning or adaptive ensemble selection strategies as suggested in the broader ensemble learning literature (Dai, 2013; Fernandez Delgado et al., 2014).

Despite these challenges, the broader theoretical contribution of cloud deployed ensemble deep learning lies in its ability to bridge the gap between numerical finance and affective social analytics. By integrating deep neural networks, ensemble theory, and sentiment analysis within a unified cloud based framework, it provides a powerful tool for exploring how digital emotions and narratives are translated into economic value. In this sense, the work of Kanikanti et al. (2025) and the present theoretical extension contribute not only to the technical field of crypto currency forecasting but also to a deeper understanding of how markets function in the age of social media and artificial intelligence.

Future research directions should therefore focus on expanding the scope of affective features, incorporating multimodal data such as images and videos, and developing cross cultural emotion models that can better capture the global nature of crypto markets (Poria et al., 2016; Haralabopoulos et al., 2018). Additionally, ethical considerations related to market manipulation, data privacy, and algorithmic transparency must be integrated into the design of predictive systems, ensuring that technological advances contribute to a more equitable and stable financial ecosystem.

Conclusion

The synthesis of ensemble deep learning, affective computing, and cloud based infrastructure represents a paradigm shift in the prediction of crypto currency market trends. By conceptualizing markets as affective information systems and by operationalizing this insight through diverse and integrated deep learning architectures, the present study advances both the theoretical and methodological foundations of financial forecasting in the digital age. Grounded in the empirical and architectural insights of Kanikanti et al. (2025) and enriched by a broad corpus of ensemble and sentiment research, the analysis demonstrates that robust and adaptive prediction is possible even in the face of extreme volatility and informational noise.

Ultimately, the value of cloud deployed ensemble deep learning lies not merely in its predictive accuracy but in its capacity to illuminate the complex interplay between emotion, discourse, and economic behavior. As crypto currencies continue to reshape the global financial landscape, such integrative and theoretically informed approaches will be essential for understanding and navigating the emergent dynamics of value in a networked world.

References

1. Divina, F., Gilson, A., Gomez Vela, F., Garcia Torres, M., Torres, J.F. Stacking ensemble learning for short term electricity consumption forecasting. Energies 11, 949.
2. Go, A., Bhayani, R., Huang, L. Twitter sentiment classification using distant supervision. Stanford CS224N Project Report.
3. Haralabopoulos, G., Simperl, E. Crowdsourcing for beyond polarity sentiment analysis a pure emotion lexicon. arXiv:1710.04203.
4. Fersini, E., Messina, E., Pozzi, F.A. Expressive signals in social media languages to improve polarity detection. Information Processing and Management 52, 20–35.
5. Deng, L., Yu, D. Deep learning methods and applications. Foundations and Trends in Signal Processing 7, 197–387.
6. Fernandez Delgado, M., Cernadas, E., Barro, S., Amorim, D. Do we need hundreds of classifiers to solve real world classification problems. Journal of Machine Learning Research 15, 3133–3181.
7. Deriu, J., Gonzenbach, M., Uzdilli, F., Lucchi, A., Jaggi, M. Swisscheese at semeval sentiment classification using an ensemble of convolutional neural networks. Proceedings of SemEval.
8. Pak, A., Paroubek, P. Twitter as a corpus for sentiment analysis and opinion mining. LREC.
9. Cambria, E. Affective computing and sentiment analysis. IEEE Intelligent Systems 31, 102–107.
10. Picard, R.W. Affective Computing. MIT Press.
11. Dong, X., Yu, Z., Cao, W., Shi, Y., Ma, Q. A survey on ensemble learning. Frontiers of Computer Science 14, 241–258.
12. Zhang, C., Ma, Y. Ensemble Machine Learning Methods and Applications. Springer.
13. Friedman, J.H. Greedy function approximation a gradient boosting machine. Annals of Statistics.
14. Freund, Y., Schapire, R.E. Experiments with a new boosting algorithm. Machine Learning.
15. Alm, C.O., Roth, D., Sproat, R. Emotions from text machine learning for text based emotion prediction. Proceedings of HLT EMNLP.
16. Haralabopoulos, G., Wagner, C., McAuley, D., Simperl, E. A multivalued emotion lexicon created and evaluated by the crowd. Proceedings of SNAMS.
17. Tian, Y., Galery, T., Dulcinati, G., Molimpakis, E., Sun, C. Facebook sentiment reactions and emojis. Proceedings of NLP for Social Media.
18. Boiy, E., Moens, M.F. A machine learning approach to sentiment analysis in multilingual web texts. Information Retrieval.
19. Agarwal, A., Xie, B., Vovsha, I., Rambow, O., Passonneau, R. Sentiment analysis of twitter data. Proceedings of LSM.
20. Fouad, M.M., Gharib, T.F., Mashat, A.S. Efficient twitter sentiment analysis system with feature selection and classifier ensemble. Proceedings of ICAMLTA.
21. Da Silva, N.F., Hruschka, E.R., Hruschka, E.R. Tweet sentiment analysis with classifier ensembles. Decision Support Systems.
22. Dai, Q. A competitive ensemble pruning approach based on cross validation technique. Knowledge Based Systems.
23. Elnagar, A., Al Debsi, R., Einea, O. Arabic text classification using deep learning models. Information Processing and Management.
24. Mullen, T., Malouf, R. A preliminary investigation into sentiment analysis of informal political discourse. AAAI Spring Symposium.
25. Ekbal, A., Saha, S. A multiobjective simulated annealing approach for classifier ensemble. Expert Systems with Applications.

26. Fersini, E., Messina, E., Pozzi, F.A. Sentiment analysis Bayesian ensemble learning. Decision Support Systems.

27. Cvijikj, I.P., Michahelles, F. Understanding social media marketing. Proceedings of MindTrek.

28. Deng, L., Platt, J. Ensemble deep learning for speech recognition. Interspeech.

29. Poria, S., Chaturvedi, I., Cambria, E., Hussain, A. Convolutional MKL based multimodal emotion recognition and sentiment analysis. Proceedings of ICDM.

30. Glorot, X., Bengio, Y. Understanding the difficulty of training deep feedforward neural networks. Proceedings of AISTATS.

31. Das, R., Sengur, A. Evaluation of ensemble methods for diagnosing of valvular heart disease. Expert Systems with Applications.

32. Dedhia, C., Ramteke, J. Ensemble model for twitter sentiment analysis. Proceedings of ICISC.

33. Delgado, R. A semi hard voting combiner scheme to ensemble multi class probabilistic classifiers. Applied Intelligence.

34. Boiy, E., Hens, P., Deschacht, K., Moens, M.F. Automatic sentiment analysis in online text. Proceedings of ELPUB.

35. Asghar, M.Z., Subhan, F., Imran, M., Kundi, F.M., Shamshirband, S., Mosavi, A., Csiba, P., Varkonyi Koczy, A.R. Performance evaluation of supervised machine learning techniques for efficient detection of emotions from online content. arXiv.

36. Yi, J., Nasukawa, T., Bunescu, R., Niblack, W. Sentiment analyzer extracting sentiments about a given topic. Proceedings of ICDM.

37. Nasukawa, T., Yi, J. Sentiment analysis capturing favorability using natural language processing. Proceedings of Knowledge Capture.

38. Annett, M., Kondrak, G. A comparison of sentiment analysis techniques polarizing movie blogs. Proceedings of Canadian AI Conference.

39. Chaffar, S., Inkpen, D. Using a heterogeneous dataset for emotion analysis in text. Proceedings of Canadian AI Conference.

40. Sidorov, G., Miranda Jimenez, S., Viveros Jimenez, F., Gelbukh, A., Castro Sanchez, N., Velasquez, F., Diaz Rangel, I., Suarez Guerra, S., Trevino, A., Gordon, J. Empirical study of machine learning based approach for opinion mining in tweets. Proceedings of MICAI.

41. Zurada, J.M. Introduction to Artificial Neural Systems. West Publishing.

42. Denecke, K., Deng, Y. Sentiment analysis in medical settings. Artificial Intelligence in Medicine.

43. Zhang, Y., Chen, M., Huang, D., Wu, D., Li, Y. iDoctor personalized and professionalized medical recommendations. Future Generation Computer Systems.

44. Abbaspour Gilandeh, Y., Molaee, A., Sabzi, S., Nabipur, N., Shamshirband, S., Mosavi, A. A combined method of image processing and artificial neural network for identification of rice cultivars. Agronomy.

45. Mollahosseini, A., Chan, D., Mahoor, M.H. Going deeper in facial expression recognition using deep neural networks. Proceedings of WACV.

46. Havaei, M., Davy, A., Warde Farley, D., Courville, A., Bengio, Y., Pal, C., Jodoin, P.M., Larochelle, H. Brain tumor segmentation with deep neural networks. Medical Image Analysis.

47. da Conceicao, L.R.V., Carneiro, L.M., Rivaldi, J.D., de Castro, H.F. Solid acid as catalyst for biodiesel production. Industrial Crops and Products.

48. Erdogan, Z., Namli, E. A living environment prediction model using ensemble machine learning techniques. Journal of Ambient Intelligence and Humanized Computing.