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Using Multi-Label Multi-Class Support Vector Machines with Semantic and Lexical Features for Aspect Category Detection

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Abstract— In contrast to the aspects, aspect categories are often coarser and don't always appear as terms in sentences. Besides, the typical way to element the types associated with part is generally grainier concerning factors and doesn't exist within verdicts. The primary intent of the study is to investigate the efficacy of Lexicon, linguistic, vector-based, and features correlated to semantics within the aspect of the responsibility built with the finding of aspect category detection ACD). Semantic and emotional data are captured via vector-based features. Further, it examines vector-based feature superiority issues within the compression of features of text-based characteristics. Study purposes to the linguistic efficacy with the Lexicon, linguistic, and semantic features, also vector-based dependent to the system. Also, the information led with vector-based features that capture the semantic with sentimental analysis characteristics. With the experimental outcomes, the performance efficacy with the vector-based features outperformed text-based features. The methodologies associated with deep learning have generated features within the vector orientation relevant to the word-based structures. Therefore, the proposed method achieved effectiveness with the determined constraints by applying the metrics of precision, recall, and F1 scores. Correlating with the performance of ABSA's state-of-the-art techniques, the proposed research process gained superior outcomes.

Keywords- Aspect category detection, ABSA, Semantic features, Vector-based features.

I. INTRODUCTION

Sentiment Analysis systems recommend commodities which likely being with the consumer. The analysis can be estimated based on the systems gained within the utility caused by the items recommended to the consumer features [1]. Before the products led to the utility for the province of the feedback gained with the customer reviewed, the thoughts set for the aspect being made through the components elementary to the ranking developed. Further, the aspect category to the terms can be oriented to the components of the products within the elements set for the reviews and recommendations. Based on the expressions of the reviewers, the features built to the opposing views of the sentimental basis, such as negative, positive, neutral, and conflicting situations. Creating specific thoughts and opinions of fine-grained attitudes seems to be more crucial due to the preferences gained through consumer preferences [2]. Therefore, driving within the influence of elementary behaviors of certain analysis created to the decisions made between the decisions and outcomes set with driving feasible for the systems. Practically, every user may not expect the product rate with the purchase rate of individual aspects categorized to the limited reviews and recommendations of the price demanded for individuals [3]. Thus, the limitation can be overcome through the supplementary divisions served through the knowledge built socially further to the development of the purchase made by user as per the improvised facility created in building the performance reached.

Sentiment Analysis systems research has grown steadily over the last decade, as evidenced by the increase in research papers in this area. Notwithstanding the research continuation within the reviews raised to the feedback systemized to progress implicitly. In progressing to the nuances linguistic with the aspects to the nature texting for the media associated within the extraction under value approached further. Extraction of aspects to the information set to the strategy assigned within the users priced decision set for the preferences implicit in feedback generated sourcing with the leveraging improving to the recommended further through the performance gained with the system set for solutions analyzed.

The research focused with the approach generated through the analyses the reviews and recommendations generating the capturing sentimental ability to the entity built with the restaurant facilities. Number of comments and reviews on an entity is much larger than our reading ability. Every product or restaurant has thousands of reviews where the customers specify their opinion on it. Several platforms such as Yelp and Amazon are trying to display opinions of customers to users by developing better ways. One of the famous techniques for display opinions summarized within the information generated through consideration developed to the limited analysis rated with the high domain gain with the technologies. Upon limited methodologies generated within the view set for the applied analysis through the cause generated to the strategies built through ABSA built within the models designed at the category aspect authenticated. In ABSA technique, the aspects are extracted automatically from the reviews of customers and define the thoughts of the reviewers about the sentiments of the aspects. Furthermore, we aggregate the information of level realized with the particular aspect attained through the analysis for beneficiary aggregation within the setup of entity in dataset associated. Thus, ABSA application is beyond the extreme constraints reached to the spaces pf the opinion utilized to understand the scope in the drives precepted to the thought analysis created in sentimental creation.

The SemEval 2014 competition addressed the ACD as a sub task of ABSA. In Aspect Category Detection, every sentence is tagged with aspect categories which are mentioned in the sentence. The FOOD, AMBIENCE, PRICE, and SERVICE are examples of aspect categories. The sentences which are not contain the previous aspect categories belongs to the aspect category of ANECDOTES / MISCELLANEOUS. For example, the sentence "The restaurant was expensive, but the menu was great" contains the aspect categories of FOOD and PRICE.

In section 2, the related work for sentiment identification, aspect terms extraction, identification of aspect term category and aspect term and aspect category sentiment polarity is presented. In section 3, various types of features used to train the machine learning algorithms to extract aspect categories for the reviews in the test dataset are explained. The dataset description, evaluation measures and comparison of results on various machine learning techniques and its analysis is presented in section 4. The section 5 presents the conclusions of this work and possible future direction to the proposed work.

II. RELATED WORK

ABSA remains as a mission which orients with the sentence determination associated in individual aspect attained through the system [4]. Every resultant service, product, or individual can elicit feedback. Within the reached to object of a person's opinion. A set of aspects can be assigned to an entity. Instance, an entity cane be created for the elementary analysis for the screen and battery division for the iPhone [5], according to Liu. Further, a thought has been generated for the entity developed to the viewpoint of individual condition, whether negative or positive, for certain entity built. Oriented with the polarity reached through the sentimental analysis attained for the element process's neutral situation can be characterized by positivity, negativity, and neutrality, with no opinion considered neutral sentiment.

The ABSA is divided into two main tasks: classification with the sentiment extraction and sentiment categorization. Further, the challenge being developed to the model requested dependent on the dataset with the task initiated through supervised learning. Moreover, the frequent noun approach uses a large dataset of product reviews to determine the product aspects expressed by noun phrases and nouns. In contrast, implicit aspect expressions are frequently identified using adjectives [6].

Popescu and Etzioni (2007) extracted a list of noun phrases and nouns from the product reviews dataset and then pruned this list based on a threshold range of width samples generated [7]. Throughout the aspects built with the assessment of the aspects comprised based on the system being determined based on Pairwise Mutual Information (PMI) among aspect of candidate with the developed sequence of the pattern collaborated to the extracted system. To identify the aspects produced by Rana and Cheah (2017) utilized through patterns of POS [8]. Noun adjectives allow you to identify and extract the associated noun. A dependency parser is used for generation of semantic relationships determination among the keywords supposed with

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the Lexicon for the sentimental approach analyzed further through the phrases developed in final outcome being developed under proximity produced with the phrases [9]. Outcome reached through the proposed system by Qiu et al. (2011) of technology constructed for propagation can be determined at individual rate of analysis under sentimental aspects [10]. Further, to begin by extracting a small-scale collection of words associated to seed sentiment words through Hu and Liu's (2004) [11]. Moreover, through sentiment lexicon. Kang and Zhou (2017) the scalar quantity has been initiated through the feasible development of the noun extracted with the limited scenarios of the inbuilt process [12]. Such commonly applied things associated with the creation of rule-based strategy can be built through Poria et al. (2014) by SenticNet in further aspects generated [13].

Qiu et al. (2011) proposed a propagation method to determine all possible aspects and sentiments [10]. They began by extracting a small set of seed sentiment words using Hu and Liu's (2004) [11] sentiment Lexicon. Kang and Zhou (2017) developed a method that does not scale well to large datasets because it extracts many noun phrases or nouns that are not aspects [12]. This is because non-opinionated adjectives will be extracted as opinion words during propagation. To identify aspects, sentiment lexicons such as SentiWordNet and Hu and Liu's sentiment lexicon are commonly used. Poria et al. (2014) created the SenticNet aspect parser, a rule-based aspect extraction algorithm that uses SenticNet as the sentiment lexicon to extract aspects [13]. Hai et al. (2014) proposed a supervised joint sentiment and aspect model to identify the usefulness of reviews at the aspect level [17]. The proposed model resembles supervised LDA. Marcheggiani et al. (2014) proposed a CRF model that can handle multiple aspects in a sentence [18]. Furthermore, when multiple aspects are present in the same sentence, they likely control each other via certain discourse elements that influence the index in every component.

Sauper and Barzilay (2013) presented a probabilistic model that performs sentiment analysis and aspect detection simultaneously for the domain of restaurant reviews and only performs aspect detection for the medical domain [19]. Mukherjee and Liu, 2012 [20] combine the MaxEnt classifier with the LDA model. The MaxEnt classifier is used to optimize the word priors influencing the drawing word generation process. Rana and Cheah (2017) identify product aspects using POS patterns [8]. Upon driving within the influence of elementary behaviors of certain analysis created to the decisions made between the decisions and outcomes set with driving feasible for the systems [21] [22]. Practically, every user may not expect the product rate with the purchase rate of individual aspects categorized to the limited reviews and recommendations of the price distributed [23].

Notwithstanding the research continuation within the reviews raised to the feedback systemized to progress implicitly. In progressing to the nuances linguistic with the aspects to the nature texting for the media associated within the extraction under value approached further. Extraction of characteristics to the information set to the strategy assigned within the user's priced decision set for the preferences implicit in feedback generated sourcing with the leveraging improving to the recommended further through the performance gained with the system set for solutions analyzed [11].

III. PROPOSED WORK

Our approach to the aspect category detection task is based on supervised Machine Learning. Our system combines many features to achieve competitive results. ACD has been formulated based on the study of classification format with a multi-system label fed to the level of review in each category. Sentences are first analyzed by the Stanford tokenizer, POS-tagger, and dependency tree extractor. Then, the pre-processed data with its word representations help determine the features that undergo the task process, as depicted in Figure 1.

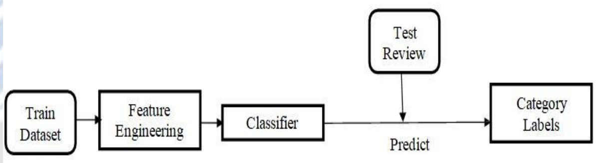

Figure 1. The Proposed System for Aspect Category Detection

The various types of features to represent the review sentence for learning the model by the classifier are presented below:

A. *Linguistic Features*

- Word N-grams: The count of word unigrams and bigrams in the sentence.
- TF-IDF: Term Frequency and Inverse Document Frequency of a word computed from the training data.

B. *Sematic Features*

The following features are used to capture the semantic relations among the words present in the corpus.

- Topic modelling: The LDA facilitates the distribution generation of the document with predefined subjects.
- Word2Vec: We used the publicly available word vectors generated through the word2vec model with dimensionality of 300, which uses Yelp restaurant dataset for training.

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- WordNet: WordNet matches the hypernym tree of every word in a sentence with the four categories: price, service, ambience and food. If the hypernym tree doesn't contain any of such categories of words, we check the next level words hypernym tree which are derived from the previous work hypernym. The frequency count of each category is listed as a feature. If these four categories are not matched in the hypernym tree, It is considered as anecdotes/ miscellaneous category.

C. *Lexicon Features*

These features are generated using Yelp Restaurant review corpus. The sentiment score of every word in the corpus is calculated utilizing Point-wise Mutual Information (PMI) system.

- Frequency count: Ranging words based on negative and positive analyses scores.
- Polarity score: sentence associated with complete score (all the words sentiment scores are summed in the sentence).
- Word2Aspect: Categorized with the individual word with the sentence at different count rates. The Association of the sentence with each category can be done through PMI.

D. *Word Vector Features*

They are utilizing the skip-gram model in Word2Vec for vector representations computation of words seeking at Yelp dataset based on restaurant reviews through the spatial distribution generated under a 300-dimensional vector area. Features followed below signify the vectors of words grouped.

- Word Vector Average (WVA): It is attained by averaging the word vector representations in the sentence. It is computed as follows:

$$WVA=\frac{\frac{1}{N}\sum_{i-1}^{N} v_i}{|\frac{1}{N}\sum_{i-1}^{N} v_i|}$$

Where, vi is the vector representation of the ith word in the sentence, N is the words count. The adverbs, adjectives, verbs and nouns are used to calculate the WVA.

- Vec2Cat: Similarity between vector and category is computed. Initially, words count has been identified for each category. Then, determine the cosine similarity among the word vectors of the input sentence and the vectors of seed words. The maximum cosine similarity among word vectors of the sentence and seed words is considered as a feature.

IV. Results and Discussions

A. *Dataset Description*

Restaurants training has the dataset which contains 3041 of English sentences which includes the annotations for aspect categories and overall sentence polarities. Additional 800 restaurant reviews were collected and annotated and used as test data. The dataset characteristics are presented in Table 1.

TABLE I. REVIEWS IN RESTAURANT TRAIN AND TEST DATASET

Domain	Train	Test	Total
Restaurant	3041	800	3841

Table 2 presents the aspect categories distribution in both training and testing datasets. The FOOD category is the dominant aspect category in both test and training restaurant sentences and the major polarity class is 'positive'

TABLE II. ASPECT CATEGORIES DISTRIBUTION IN TRAIN AND TEST DATASETS

Category	Train	Test	Total
FOOD	1232	418	1650
PRICE	321	83	404
SERVICE	597	172	769
AMBIENCE	431	118	549
MISCELLANEOUS	1132	234	1366
Total	3713	1025	4738

In this dataset sourced, the aspects categorized under that are predefined parameters that are characterized into FOOD, SERVICE, AMBIENCE, PRICE AND ANECDOTES/MISCELLANEOUS.

Certain with the category distributed with datasets assigned as listed in table 3 shown. Table 4 displays the percentage of the distribution of number of categories over reviews. Numerous system reviews are classified into individual component based on interest served by the user.

TABLE III. REVIEW RANGE BASED ON SUBSET CENTROIDED UNDER MULTIPLE CLASSIFICATIONS

#Cats	Train	Test
1	2465	611
2	486	155
3	84	32
4	6	2

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TABLE IV. REVIEW VALUE IN % BASED ON SUBSET CENTROIDED UNDER MULTIPLE CLASSIFICATIONS

#Cats	Train (%)	Test (%)
1	81%	76%
2	15%	19%
3	2%	4%
4	0.1%	0.2%

B. *Evaluation Measures*

The F1 measure is computed as

Where R is a Recall and P is a Precision. The P and R is defined as

$$R = \frac{|S \cap G|}{|G|} \qquad P = \frac{|S \cap G|}{|S|}$$

$$F1 = \frac{2 * P * R}{P + R}$$

Here, G is the set of correctly annotated aspect categories and S is the set of aspect category annotations that a system returned from all the test sentences.

C. *Empirical Evaluations*

Due to the analysis generated by sentence that categorizes with multi-label one-vs-all Support Vector Machines (SVMs) systems observed in occurrence to the general design. We treat this subtask for the sentence. Each sentence can have multiple categories. A 10-fold cross validation is performed on training dataset with default C value.

Further, implementation with J48, as decision tree algorithm sets for constructing the Information entropy formulation. The algorithm uses information gain measure to choose the most informative features. Naive Bayes (NB) classifier works based on Bayes rule.As a classifier division, IBk integrated to K-Nearest Neighbor (KNN) classifier. Further, generates the computation among the vectors dimensioned through the sample created within attained and validated counts. The label of the unseen example is based on the k nearest neighbors training examples. Upon the development of Weka 2.7 implementation of J48, IBk and Naive Bayes applied within the range of 5 as attribute to k. Certainly, the classifier performance can be assigned within linguistic, semantic, Lexicon and word vector features are evaluated on restaurant dataset with 10-fold cross-validation and the results are displayed in Table 5. We allocate anecdotes/ miscellaneous category for the words which are not belonging to any of the four categories.

From the results, it is found that the semantic features improve the performance of the system 7.5 % for multi-class multi label SVM implementation. The impact of Lexicon based features increases the F1 score by 8.8 %. The vector-based features impact is increasing the performance of the system compared with text based features is 18.1%. Summing with vector-based features to the lexicon features, Semantic based features and linguistic features increases the F1-score by 1.8%. The performance of the decision Tree implementation is also comparable with SVM implementation. The performance of K-Nearest Neighbor implementation is low compared with the remaining three algorithms.

TABLE V. OUTCOMES OF ASPECT CATEGORY DETECTION ON RESTAURANT DATASET

Classifier	Features	Precision	Recall	F1-Score
Support Vector Machine	Linguistic	78.3	67.8	72.7
	+ Semantic	84.5	76.4	80.2
	+ Lexicon	90.8	87.3	89.0
	+ Word Vector	93.2	88.6	90.8
Decision Tree	Linguistic	76.7	65.9	70.9
	+ Semantic	82.8	74.3	78.3
	+ Lexicon	88.5	83.8	86.1
	+ Word Vector	91.5	85.2	88.2
Naive Bayes	Linguistic	76.3	64.8	70.1
	+ Semantic	81.6	72.9	77.0
	+ Lexicon	86.2	79.6	82.7
	+ Word Vector	89.4	83.7	86.4
K-Nearest Neighbor	Linguistic	77.6	63.7	69.9
	+ Semantic	80.2	70.6	75.1
	+ Lexicon	84.7	77.2	80.7
	+ Word Vector	88.9	82.5	85.5

The comparison among four classifiers with the combination of all features is presented in Figure 2. The results found that the F1-score for the SVM classifier, NB classier, IBk classier and J48 classier is 90.8 %, 86.4%, 88.2% and 85.5%, respectively.

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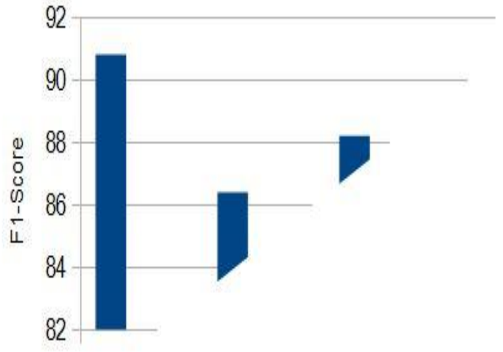

Figure 2.The combination of all features of the F- 1 Score

NRC-Canada is the top performing system for the Aspect Category Detection sub-task. The proposed method is compared with the baseline system given by the SemEval 2014 organizers for the Aspect Category Detection sub-task of ASBA. For a given sentence, the baseline system identifies the K number of sentences similar to the data trained for the system associated with the coefficient of Dice obtained through the words developed (Pontiki et al., 2014). Finally, the most frequent aspect categories which are appeared in the K retrieved sentences are used to tag the input sequence. This approach has a limitation in that it measures the semantic similarity among the sentences by employing the text-based similarity measure. The NRC-Canada system relied on five binary SVMs for every aspect category.

The proposed method improves its performance by 2.2 % compared with the top performing system at SemEval 2014 conference. Further, features with SVM are based on information from a lexicon learned from YELP data and various types of n-grams. The comparison of these two systems with the proposed system is presented in Table 6.

TABLE VI. COMPARISON WITH STATE-OF-THE-ART METHODS

Method	**Precision**	**Recall**	**F1-Score**
Baseline	70.2	61.5	65.6
NRC-Canada	91.1	86.3	88.6
Proposed System	93.2	88.6	90.8

V. CONCLUSION

The research study addressed challenges in Aspect Category Detection in ABSA. Besides, empirical evaluations are performed on four classifiers: SVM, DT, NB and KNN. These classifiers are trained using linguistic features, Semantic features, Lexicon features and vector-based features. The performance of the classifiers is measured using F1-Score. From the results, it is observed that vector-based characteristics highly influence system performance. The vector-based features, semantic features, and lexicons features encapsulate relationships among specific analyses built with the review model generated further through the trained generation of relations with the establishment of semantic characteristics on the serviced design of words that are demonstrated using the dataset of Yelp restaurant with meaningful parameters. In future, more convenient features will be included to improve the accuracy of our system. For future work, it would be interesting to explore sentiment lexicons specific to the domain to improve the performance and examine more advanced ways of using sentiment lexicons and word embedding features.

VI. REFERENCES

[1] Ahammad, S.H., Rajesh, V., Rahman, M.Z.U., Lay-Ekuakille, A., "A Hybrid CNN-Based Segmentation and Boosting Classifier for Real Time Sensor Spinal Cord Injury Data", IEEE Sensors Journal,20(17), pp. 10092-10101.

[2] Inthiyaz, S., Prasad, M.V.D., Usha Sri Lakshmi, R., Sri Sai, N.T.B., Kumar, P.P., Ahammad, "Agriculture based plant leaf health assessment tool: A deep learning perspective", S.H., International Journal of Emerging Trends in Engineering Research 7(11), pp. 690-694.

[3] Kumar, M.S., Inthiyaz, S., Vamsi, C.K., Ahammad, S.H., Sai Lakshmi, K., Venu Gopal, P., Bala Raghavendra, A., "Power optimization using dual sram circuit",International Journal of Innovative Technology and Exploring Engineering 8(8), pp. 1032-1036.

[4] Hasane Ahammad, S., Rajesh, V., Hanumatsai, N., Venumadhav, A., Sasank, N.S.S., Bhargav Gupta, K.K., Inithiyaz,"MRI image training and finding acute spine injury with the help of hemorrhagic and non hemorrhagic rope wounds method", Indian Journal of Public Health Research and Development 10(7), pp. 404-408.

[5] Siva Kumar, M., Inthiyaz, S., Venkata Krishna, P., Jyothsna Ravali, C., Veenamadhuri J., Hanuman Reddy, Y., Hasane Ahammad, S.,"Implementation of most appropriate leakage power techniques in vlsi circuits using nand and nor gate", International Journal of Innovative Technology and Exploring Engineering 8(7), pp. 797-801.

[6] Myla, S., Marella, S.T., Goud, A.S., Ahammad, S.H., Kumar, G.N.S., Inthiyaz, S.," Design decision taking system for student career selection for accurate academic system", International Journal of Scientific and Technology Research 8(9), pp. 2199-2206.

[7] Raj Kumar, A., Kumar, G.N.S., Chithanoori, J.K., Mallik, K.S.K., Srinivas, P., Hasane Ahammad, S., "Design and analysis of a heavy vehicle chassis by using E-glass epoxy & S-2 glass materials" International Journal of Recent Technology and Engineering 7(6), pp. 903-905.

[8] Gattim, N.K., Pallerla, S.R., Bojja, P., Reddy, T.P.K., Chowdary, V.N., Dhiraj, V., Ahammad, S.H., "Plant leaf disease detection using SVM technique", International

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Journal of Emerging Trends in Engineering Research, 7(11), pp. 634-637.

[9] Myla, S., Marella, S.T., Swarnendra Goud, A., Hasane Ahammad, S., Kumar, G.N.S., Inthiyaz, S., “Design decision taking system for student career selection for accurate academic system”, International Journal of Recent Technology and Engineering, 8(9), pp. 2199-2206.

[10] Ahammad, S.H., Rajesh, V., Venkatesh, K.N., Nagaraju, P., Rao, P.R., Inthiyaz, S., “Liver segmentation using abdominal CT scanning to detect liver disease area”,International Journal of Emerging Trends in Engineering Research, 7(11), pp. 664-669.

[11] Srinivasa Reddy, K., Suneela, B., Inthiyaz, S., Hasane Ahammad, S., Kumar, G.N.S., Mallikarjuna Reddy, A., “Texture filtration module under stabilization via random forest optimization methodology”, International Journal of Advanced Trends in Computer Science and Engineering, 8(3), pp. 458-469.

[12] Narayana, V.V., Ahammad, S.H., Chandu, B.V., Rupesh, G., Naidu, G.A., Gopal, G.P., “Estimation of quality and intelligibility of a speech signal with varying forms of additive noise”, International Journal of Emerging Trends in Engineering Research, 7(11), pp. 430-433.

[13] Poorna Chander Reddy, A., Siva Kumar, M., Murali Krishna, B., Inthiyaz, S., Ahammad, S.H., “Physical unclonable function based design for customized digital logic circuit”, International Journal of Advanced Science and Technology, 28(8), pp. 206-221.

[14] Rama Chandra Manohar, K., Upendar, S., Durgesh, V., Sandeep, B., Mallik, K.S.K., Kumar, G.N.S., Ahammad, S.H. , “Modeling and analysis of Kaplan Turbine blade using CFD”, International Journal of Engineering and Technology (UAE), 7(3.12 Special Issue 12), pp. 1086-1089.

[15] Nagageetha, M., Mamilla, S.K., Hasane Ahammad, S., “Performance analysis of feedback based error control coding algorithm for video transmission on wireless multimedia networks”, Journal of Advanced Research in Dynamical and Control Systems, 9(Special Issue 14), pp. 626-660.

[16] Ahammad SH, Rahman MZ, Rao LK, Sulthana A, Guptha N, Lay-Ekuakille A. A Multi-Level Sensor based Spinal Cord disorder Classification Model for Patient Wellness and Remote Monitoring. IEEE Sensors Journal. 2020 Jul 28.

[17] Myla, S., Marella, S.T., Swarnendra Goud, A., Hasane Ahammad, S., Kumar, G.N.S., Inthiyaz, S., “Design decision taking system for student career selection for accurate academic system”, International Journal of Recent Technology and Engineering, 8(9), pp. 2199-2206.

[18] Srinivasa Reddy, K., Suneela, B., Inthiyaz, S., Hasane Ahammad, S., Kumar, G.N.S., Mallikarjuna Reddy, A., “Texture filtration module under stabilization via random forest optimization methodology”, International Journal of Advanced Trends in Computer Science and Engineering, 8(3), pp. 458-469.

[19] Murthy, A. S. D., Murthy, P. S., Rajesh, V., Ahammad, S. H., & Jagan, B. O. L. (2019). Execution of natural random forest machine learning techniques on multi spectral image compression. International Journal of Pharmaceutical Research, 11(4), 1241-1255.

[20] Ahammad, S.H., Rajesh, V., Rahman, M.Z.U., Lay-Ekuakille, A., "A Hybrid CNN-Based Segmentation and Boosting Classifier for Real Time Sensor Spinal Cord Injury Data", IEEE Sensors Journal,20(17), pp. 10092-10101.

[21] Raj Kumar, A., Kumar, G.N.S., Chithanoori, J.K., Mallik, K.S.K., Srinivas, P., Hasane Ahammad, S., “Design and analysis of a heavy vehicle chassis by using E-glass epoxy & S-2 glass materials” International Journal of Recent Technology and Engineering 7(6), pp. 903-905.

[22] Myla, S., Marella, S.T., Goud, A.S., Ahammad, S.H., Kumar, G.N.S., Inthiyaz, S.,” Design decision taking system for student career selection for accurate academic system”, International Journal of Scientific and Technology Research 8(9), pp. 2199-2206.

[23] Ahammad, S. H., Rajesh, V., & Rahman, M. Z. U. (2019). Fast and accurate feature extraction-based segmentation framework for spinal cord injury severity classification. IEEE Access, 7, 46092-46103.

[24] Jindal, N. and Liu, B. (2008). Opinion spam and analysis. In Proceedings of the 2008 International Conference on Web Search and Data Mining, pages 219–230. ACM.

[25] Moghaddam, S. and Ester, M. (2012). On the design of lda models for aspect-based opinion mining. In Proc. Inter. Conf. on Information and Knowledge Management, CIKM '12.

[26] Qiu, G., Liu, B., Bu, J., and Chen, C. (2011). Opinion word expansion and target extraction through double propagation. Computational linguistics, 37(1):9–27.