Plant Archives Vol. 20, Supplement 2, 2020 pp. 2673-2677 **e-ISSN:2581-6063 (online), ISSN:0972-5210**

PREDICTION OF BIO-OIL PRODUCTION FROM BIOMASS BY USING EXPERIMENTAL PYROLYSIS TECHNIQUE AND THEORETICAL ESTIMATION BY USING MACHINE LEARNING TECHNIQUES

A.P.Singh Chouhan[1], S.P.Singh[2]

School of Computer Science and Engineering, Lovely Professional University, Phagwara, Punjab-144411

School of Energy & Environmental Studies, Devi AhilyaVishwavidyalaya, Indore-452017, M.P.

Abstract

This study presents the pyrolysis of selected four agricultural wastes and wood forestry waste performed at 600 ^oC temperature in electrically heated tubular reactor in nitrogen environment and carried out bio-oil, charcoal and pyro gases. Experimentally production of bio-oil depends on the affective parameters like biological contents, ultimate and proximate analysis so that efforts were made to predict the bio-oil production on the basis of affecting input parameters of the biomass and operating parameters of the reactor by using statics based machine learning methods (linear regression, multilayer perceptron analysis and support vector machine).

Keywords: Biomass wastes, bio-oil, pyrolysis, neural network, linear regression, SVM method.

Introduction

Pyrolysis is a degradation of biomass at high temperature in oxygen free environment, it is a type of thermo-chemical conversion process and pyrolysis can provide promising solution of the conversion of biomass into clean and renewable energy but designing of the pyrolysis reactor is very challenging due to the complexity in the designing of the pyrolysis reactor due to heat transfer mechanism, cost feasibility of the process and efficiency of the pyrolysis reactor. Some effective pyrolysis reactors were discussed in the reported literature, these are fixed bed reactor (Biswas *et al*., 2018; Wang *et al*., 2005), fluidized bed pyrolysis reactor (Boateng *et al*., 2007), circulating fluidized bed pyrolysis reactor (Velden *et al*., 2007), auger pyrolysis reactor (Ingram *et al*., 2008) etc. The bio-oil generation by using pyrolysis were dependent on the heating temperature, heating rate, sweep gas flow rate, residence time and internal characteristics of the selected biomass such as biological contents, ultimate analysis proximate analysis, alkali metal test . It was reported that input parameters can be played wider role for bio-oil production (Raveendran *et al*., 1995). In this article, efforts were made to carried out the bio-oil production Through the experimental pyrolysis process of selected biomass (agricultural waste and forestry waste). All of these biomass materials first pyrolyzed andperceptron methods. All of these methods met to report the training and validation of the output results were similar to the experimental methods.

Generally linear regression is working on the basis of correlation between dependent and independent variables of the inputs and output, dependency of the input response on the regressors is known as linear function. Support vector machine (SMO) consists of a small subset of data points classified by the learning algorithm from the training input samples. It is working on the principle of classification of the data points by the kernel method and multilayer perceptron was introduced in 1985. Multilayer perceptron consists nodes and it is subdivided into input layer, hidden layer and output layer, network trained by using the activation function (sigmoid, logsigmoid etc.) (Haykin *et al*., 2009). Technological Assessment and Modeling of Energy-Related CO_2 Emissions for G8 countries using SVM method is also proposed (Ghazvini *et al.,* 2019).

Materials and Methods

(A) Data Collection

The selected agricultural wastes were wood wastes, all the samples dried and prepared 212 μm sizes for the characterization and was stored for the pyrolysis.

(B) Experimental

Bio-oil were carried out by using experimental pyrolysis analysis, at controlled temperature, it is given in Fig. 1.

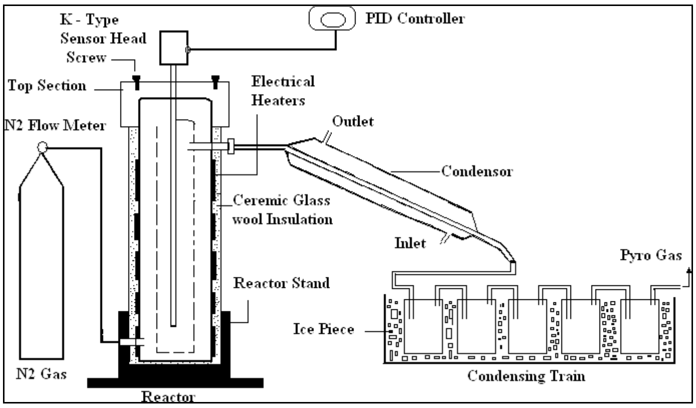

Fig. 1: Schematic diagram of pyrolysis reactor

Pyrolysis performed in tubular electrical based reactor which is mentioned in Fig.1.

(C) Prediction of Bio-oil production

Theoretical prediction of bio-oil carried out by using Java based Weka software (version 3.9.3), it is free software made by University of Waikato, New Zealand. It supported to data mining methods such as data re-processing, classification, clustering, regression, multilayer perceptron, random forest, tree methods etc. but in this study represented linear regression, multilayer perceptron and support vector machine (Chouhan, 2019; Jamil *et al*., 2016).

(I) Multilayer Perceptron Method

The main parts of the multilayer perceptron are inputs, hidden layer and single output, it is a nonlinear activation function, and hidden layers connected with inputs and output nodes. Network represents the high connectivity and scope of network is determined by synaptic weights. In this article data trained by feed-backward network. In feed-backward network(Tuya *et al.*, 2004; Ahmadi *et al.*, 2019; Saini *et al.*, 2019; Ghazvini *et al.*, 2019; Bharat *et al.*, 2019; Pawar *et al.*, 2019; Mittal *et al.*, 2019; Sethi *et al.*, 2019; Singh *et al.*, 2019; Khamparia *et al.*, 2019; Sethi *et al.*, 2016).

(II) Linear Regression Method

It is working on the basis of correlation between independent (X) and dependent(Y) variables of selected samples, mathematical equation discussed below:

$$Y = \beta o + \beta 1X \qquad \ldots(1)$$

Where βo is the intercept and β_1 is the regression coefficient (Jacqu *et al.*, 1983, Kumar *et al.*, 2019,Gitanjali *et al.*, 2019).

(III) Support vector machine (SMO) method

It is smart method which is working on the basis of convex optimization and it can define optimality of the machine. It is Lagragian based method, its formulation based on searching the optimal hyerplane start with a statement, it can be solved the optimization problems in the dual space of the Lagrange multipliers (Michie *et al.*, 1994). Where, training sample $((Y_i, D_i)^N{}_{i=1})$, and optimazation of constraints is given below

$$Di(m^T Yi + B) \qquad \ldots(1)$$

$$Di(M^T + B) \geq 1 \; fori = 1,2,\ldots..N \qquad \ldots(2)$$

And the weight vector m minimizes the cost function

$$X(m) = \frac{1}{2} m^T m \qquad \ldots(3)$$

Result and Discussion

Bio-oil Production:

The bio-oil generated by using pyrolysis process discussed below in Fig. 2.

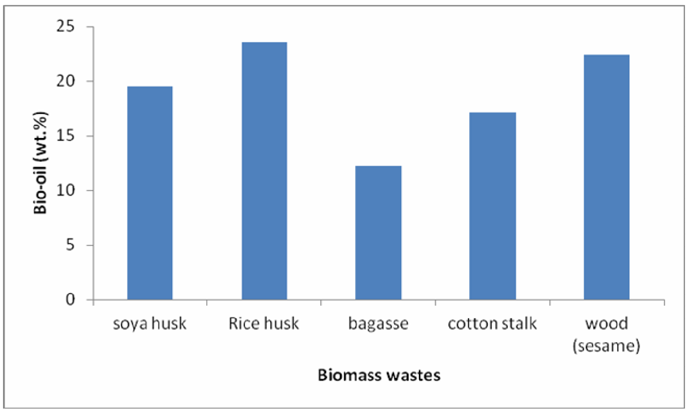

Fig. 2: Bio-oil productions through pyrolysis technique

Rice husk and wood (sesame) has good potential for bio-oil production due to the high volatile matter and carbon contents. Emission of high volatiles into the biomass due to the hellocellulose content can be enhancing the bio-oil (Özyu-uran *et al.*, 2017).

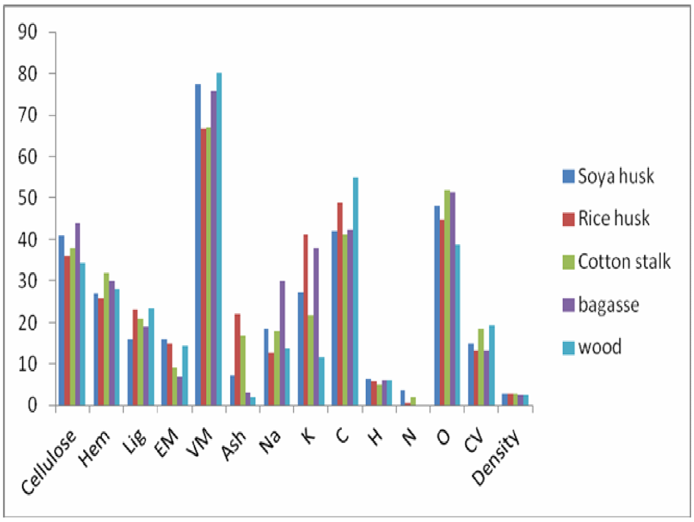

Fig. 3: Biomass characterization

Fig.3, bio-oil production highly depedenent on the characterization of bio-oil for optimization of bio-oil production, the volatile matter and carbon content should be enhanced and ash content should be minimized (Chiaramonti *et al.*, 2007). The holocellulose content (combination of cellulose and hemicelluloses) increased the emission of volatiles and also enhanced the production of bio-oil. Presence of Lignin content increased the ash content and minimized the bio-oil production (Yang *et al.*, 2007,Chouhan *et al.*, 2013).

Prediction of bio-oil by using machine learning methods

Linear Regression Method

Linear regression equation generated by the weka, it is given below:

Bio-oil = ((0.0907 * C) + (1.2156 * H) + (-0.1466 * O) + (0.0796) * AS + (-0.1641) * Cell + (-0.6639) * Hem + (-0.1517) * Na + 41.8656)

Error analysis shown in Table 1, which is given above. It was indicated that R^2 value calculated 1, and actual (experimental) and predicted data are similar and validation of the model is accurate due to the error calculations(Kumar *et al.*, 2019).

Fig. 3 : Bio-oil production by using support vector machine

Instances	1	2	3	4	5
Actual	19.51	23.52	12.19	17.14	22.41
Predicted	19.492	23.515	12.208	17.148	22.392
error	-0.018	-0.005	0.018	0.008	-0.018
Timetaken	0.02	0.02	0.02	0.02	0.02
R^2	1	1	1	1	1
MAE (%)	0.0133	0.0133	0.0133	0.0133	0.0133
RMSE (%)	0.0144	0.0144	0.0144	0.0144	0.0144
RAE (%)	0.39%	0.39%	0.39%	0.39%	0.39%

Multilayer Perceptron Method

Multilayer perceptron equation is representedbelow and results have been reported in the Table 2. The multilayer perceptron networking has been represented in Fig.4.

Bio-oil output = (+ 0 * (normalized) T + 0 * (normalized) HR + 0 * (normalized) RT + 0.1588 * (normalized) C + 0.142 * (normalized) H +(- 0.0194) * (normalized) N + (- 0.1787) * (normalized) O + (- 0.0266) * (normalized) VM + (- 0.158) * (normalized) FC + 0.1111 * (normalized) AS - 0.107 * (normalized) Cell+ (- 0.2423) * (normalized) Hem + 0.0581 * (normalized) Lig + 0.0041 * (normalized) EM (%)+ (- 0.2097) * (normalized) Na + (0.0007) * (normalized) K + 0.8093)

For this analysis data classified by using kernel classification, number of kernel evaluation was 15 and cached 90.566% data. Fig. 4 represented the multiple input nodes and 1 hidden layer and it generated 1 output and R^2 value was 0.96 for the networking and meanabsolute error (3.65%), root mean square error (4.2%) and relative absolute error (106.45%) were calculated by the weka classifier model. These results were very similar to the reported results (Jilte *et al.*, 2019, Ahmd *et al.*, 2019, Takyi *et al.*, 2019, Kaur *et al.*, 2019,Khamparia *et al.*, 2019, (More *et al.*, 2019, Rhmann *et al.*, 2019, Pandey *et al.*, 2018, Pandey *et al.*, 2019, Dhawan *et al.*, 2011,Takkar *et al.*, 2017).

Fig. 3 : Bio-oil production by using support vector machine

Instances	1	2	3	4	5
Actual	19.51	23.52	12.19	17.14	22.41
Predicted	19.492	23.515	12.208	17.148	22.392
error	-0.018	-0.005	0.018	0.008	-0.018
Time taken	0.02	0.02	0.02	0.02	0.02
R^2	1	1	1	1	1
MAE (%)	0.0133	0.0133	0.0133	0.0133	0.0133
RMSE (%)	0.0144	0.0144	0.0144	0.0144	0.0144
RAE (%)	0.39%	0.39%	0.39%	0.39%	0.39%

Table 1: Linear regression analysis for bio-oil production

Instances	1	2	3	4
Actual	19.51	23.52	12.19	17.14
Predicted	19.51	23.52	12.19	17.14
error	0	0	0	0
Time taken	0.01	0.01	0.01	0.01
R^2	1	1	1	1
MAE (%)	0	0	0	0
RMSE (%)	0	0	0	0
RAE (%)	0	0	0	0

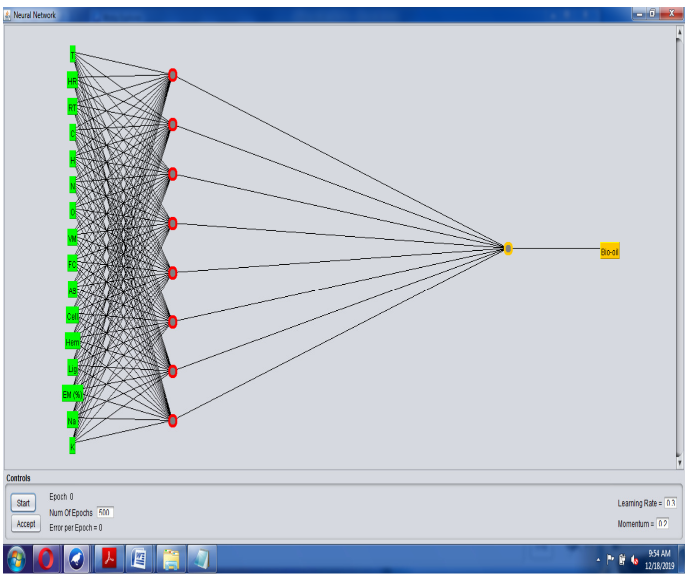

Fig.4: Multilayer perceptron network

Support vector machine (SMO) method

Equation of bio-oil prediction = (+ 0 * (normalized) T + 0 * (normalized) HR + 0 * (normalized) RT + 0.1588 * (normalized)C + 0.142 * (normalized) H + (- 0.0194) * (normalized) N + (- 0.1787) * (normalized) O + (- 0.0266) * normalized) VM + (- 0.158) * (normalized) FC + 0.1111 * (normalized) AS + (- 0.107) * (normalized) Cell + (- 0.2423) * (normalized) Hem + 0.0581 * (normalized) Lig + 0.0041 * (normalized) EM (%)+(- 0.2097) * (normalized) Na + 0.0007 * (normalized) K + 0.8093).

Table 3, which is given below indicated that R^2 value calculated 1 for the generation of output bio-oil and where observed mean square error (0.0133%), root mean square error (0.0144%) and relative absolute error (0.3866%). All of these models are very accurate but linear regression and SMO (support vector machine) predicted the similar results like experimental.

Conclusion

Experimentally production of bio-oil depends on the affective parameters like biological contents, ultimate and proximate analysis so that efforts were made to predict the bio-oil production on the basis of affecting input parameters of the biomass and operating parameters of the reactor by using statics based machine learning methods (linear regression, multilayer perceptron analysis and support vector machine) and after the model analysis it was observed that linear regression and SMO model were more accurate and predicted the similar results as experimental and error calculations were observed very minimum.

Acknowledgement

Authors are highly thankful to the assistance and provide the lab facilities by the School of Energy andEnvironmental Studies, Devi Ahilya Vishwavidyalaya Indore, Madhya Pradesh, India.

References

Ahmad, G. and Singla, J. (2019). Machine Learning Languages Techniques for Sentiment Analysis of Indian. Intern. Jour. of Rec. Technol. and Eng. (IJRTE) ISSN: 2277-3878, 8(2S11), September 2019.

Ahmad, G. and Singla, J. (2019). Machine Learning Languages Techniques for Sentiment Analysis of Indian. Intern. Jour. of Rec. Technol. and Eng. (IJRTE) ISSN: 2277-3878, 8(2S11) September 2019.

Ahmadi, M.H.; Mohseni-Gharyehsafa, B.; Farzaneh-Gord, M.; Jilte, R.D.; Kumar, R. and Chau, K. (2019). Applicability of connectionist methods to predict dynamic viscosity of silver/water nanofluid by using ANN-MLP, MARS and MPR algorithms, Eng. Appl.Comp. Fluid Mechan.; 13(1): 220-228.

Ahmadi, M.H.; Mohseni-Gharyehsafa, B.; Ghazvini, M.; Goodarzi, M.; Jilte, R. and Kumar, R. (2019). Comparing various machine learning approaches in modeling the dynamic viscosity of CuO/water nanofluid. Jour. of Ther. Anal. and Calorim.; 1-15.

Bharat, V. and Malik, N. (2019). Study of Detection of Various types of Cancers by using Deep Learning: A Survey. Intern. Jour. of Advan. Tren. in Comp. Sci. and Eng. 8(4):1228-1233.

Bharat, V. and Malik, N. (2019). Study of Detection of Various types of Cancers by using Deep Learning: A Survey. Intern. Jour. of Advan. Tren. in Comp. Sci. and Eng. 8(4):1228-1233.

Biswas, B.; Singh, R.; Kumar, J.; Singh, R.; Gupta, P.; Krishna,B.B.; Bhaskar,T. (2018). Pyrolysis behavior of rice straw under carbon dioxide 2 for production of bio-oil. Renewable Energy, 129, part B: 686-694.

Boateng, A.A.; Daugaard, D.E.; Goldberg, N.M.; Hicks, K.B. (2007). Bench-scale fluidized-bed pyrolysis of switchgrass for bio-oil production. Industrial & Engineering Chemistry Research. 46, 1891–1897.

Chiaramonti, D.; Oasmaa, A. and Solantausta, Y. (2007). Power generation using fast pyrolysis liquids from biomass. Renewable and Sustainable Energy Review, 11(6): 1056-1086.

Chouhan, A.P. (2019). Estimation of Bio-Oil Production By Using Affecting Parameters of Biomass Waste Through Stastitical Method. Think Ind. Jour.; *22*(17): 329-336.

Chouhan, A.P. and Sarma, A.K. (2013). Critital analysis of parameters for bio-oil via pyrolysis of biomass: A review. Recent Patents of Engineering, 7(2):98-114.

Dhawan, A.K. and Singh, J. (2011). Modeling and designing of machine learning procedures as applied to game playing using artificial intelligence. Proceedings of the International Conference on Advances in Computing and Artificial Intelligence – ACAI, ACM 978-1-4503-0635-5.

Dhawan, A.K. and Singh, J. (2011). Modeling and designing of machine learning procedures as applied to game playing using artificial intelligence. Proceedings of the International Conference on Advances in Computing and Artificial Intelligence – ACAI, ACM 978-1-4503-0635-5.

Ghazvini, M.; Maddah, H.; Peymanfar, R.; Ahmadi, M. and Kumar, R. (2019). Experimental evaluation and artificial neural network modeling of thermal conductivity of water based nanofluid containing magnetic copper nanoparticles. Physica A, S0378-4371(19): 32278-2.

Ghazvini, M.; Maddah, H.; Peymanfar, R.; Ahmadi, M. and Kumar, R. (2019). Experimental evaluation and artificial neural network modeling of thermal conductivity of water based nanofluid containing magnetic copper nanoparticles. Physica A, S0378-4371(19)32278-2.

Ghazvini, M.; Madvar, M.D.; Ahmadi, M.H.; Rezaei, M.H.; Assad, M.E.I.; Nabipour, N.; Kumar R. (2020). Technological Assessment and Modeling of Energy-Related CO_2 Emissions for G8 countries by Using Hybrid IWO Algorithm based on SVM, Energy Science and Engineering, 1-24.

Gitanjali, L.K. (2019). A Novel Approach of Sensitive Data Classification using Convolution Neural Network and Logistic Regression. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8(8).

Gitanjali, L.K. (2019). A Novel Approach of Sensitive Data Classification using Convolution Neural Network and Logistic Regression. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8(8).

Haykin, S. (2009). Book:edition 3rd , Pearson Education neural networks and learning machines, , Inc.; Upper Saddle River, New Jersey.

Ingram,L.; Mohan, D.; Bricka, M.; P. Steele, D. Strobel, D. Crocker,‖ B. Mitchell, J. Mohammad, K. Cantrell, Pittman, C.U. (2008). Pyrolysis of Wood and Bark in an Auger Reactor: Physical Properties and Chemical Analysis of the Produced Bio-oils", Journal of Energy & Fuels, vol.22: 614–625.

Jacquet, P.; Leonard, A. (1983). Annual book of ASTM standards. American Society for Testing of Materials. USA International.

Jamil, L.S. (2016). Data analysis based on data mining algorithms using weka Workbench. International journal of engineering sciences & research technology, 5(8): 262-267.

Kaur, P.; Agrawal, P.; Singh, S.K. and Jain, L. (2019). Fuzzy rule based students performance analysis expert system Intern. Conf. on Iss. Challeng. In intell. Comp. Techn. (ICICT), IEEE, 978-1-4799.

Kaur, P.; Agrawal, P.; Singh, S.K. and Jain, L. (2019). Fuzzy rule based students performance analysis expert system Intern. Conf. on Iss. Challeng. In intell.Comp. Techn. (ICICT), IEEE, 978-1-4799.

Khamparia, A. and Singh, K. (2019). A systematic review on deep learning architectures and applications. Exp. Sys.12400, 1-22.

Khamparia, A. and Singh, K. (2019). A systematic review on deep learning architectures and applications. Exp. Sys.12400, 1-22.

Khamparia, A.; Singh, A.; Luhach, A.; Pandey, B. and Pandey, D.K. (2019). Classification and Identification of Primitive Kharif Crops using Supervised Deep Convolutional Networks. Sust. Comp.: Inform. and Sys. xxx–xxx.

Khamparia, A.; Singh, A.; Luhach, A.; Pandey, B.; Pandey, D.K. (2019). Classification and Identification of Primitive Kharif Crops using Supervised Deep Convolutional Networks. Sust. Comp.: Inform. and Sys. xxx–xxx.

Kumar R.; Jilte R.; Nikam K.C.; Ahmadi, M.H. (2019). Status of carbon capture and storage in India's coal fired power plants: A critical review. Environmental Technology & Innovation, 13: 94–103.

Kumar, A. and Swami, R. (2019). Automated web development: theme detection and code generation using Mix-NLP. Conference: the Third International Conference, 10.1145/3339311.3339356.

Kumar, A. and Swami, R. (2019). Automated web development: theme detection and code generation using Mix-NLP. Conference: the Third International Conference, 10.1145/3339311.3339356.

Kumar, R.; Jilte, R.; Ahmadi, M.H. and Kaushal, R. (2019). A simulation model for thermal performance prediction of a coal-fired power plant. Intern. Jour. of Low-Carbon Technol. 1–13.

Michie, D.; Spiegelhalter, D.J.; Taylor, C.C. (1994). Book, Machine learning, neural and statistical classification.

Mittal, U.; Srivastava, S. and Chawla, P. (2019). Review of different techniques for object detection using deep learning. ICAICR_'19:_Proc._of_the_Third_Intern._Conf. on_Adv._Info._for_Comp. (46)1-8.

Mittal, U.; Srivastava, S. and Chawla, P. (2019). Review of different techniques for object detection using deep learning. ICAICR_'19:_Proc._of_the_Third_Intern._Conf. on_Adv._Info._for_Comp. (46): 1-8.

More, S. and Singla, J. (2019). Machine Learning Techniques with IoT in Agriculture. Intern. Jour. of Advan. Tren. in Comp. Sci. and Engin. 8(3): 742–747.

More, S. and Singla, J. (2019). Machine Learning Techniques with IoT in Agriculture. Intern. Jour. of Advan. Tren. in Comp. Sci. and Engin. 8(3): 742–747.

Özyu-uran, A. and Yaman, S. (2017). Prediction of Calorific Value of Biomass from Proximate Analysis, Proceeding of 3rd International Conference on Energy and Environment Research, ICEER September Barcelona, Spain, Energy Procedia, 130 – 136.

Pandey, B.; Bhanodia, P.K.; Khamparia, A. and Pandey, D.K. (2019). A comprehensive survey of edge prediction in social networks: Techniques, parameters and challenges. Exp. Sys. With Appl. 124: 164–181.

Pandey, B.; Bhanodia, P.K.; Khamparia, A. and Pandey, D.K. (2019). A comprehensive survey of edge prediction in social networks: Techniques, parameters and challenges. Exp. Sys. With Appl. 124: 164–181.

Pandey, D.K. and Kaur, P. (2018). Optimization of extraction parameters of pentacyclic triterpenoids from *Swertiachirata* stem using response surface methodology. Biotech 8:152.

Pandey, D.K. and Kaur, P. (2018). Optimization of extraction parameters of pentacyclic triterpenoids from *Swertiachirata* stem using response surface methodology. Biotech 8:152.

Pawar, P.; Devendran,_V. and _Singh, S. (2019). Deep learning based glance of real world scenes through decision tree. Conf.: the Third Intern. Conf. 10.1145/3339311.3339360.

Pawar, P.; Devendran,_V. and_Singh, S. (2019). Deep learning based glance of real world scenes through decision tree. Conf.: the Third Intern. Conf. 10.1145/3339311.3339360.

Raveendran, K.; Ganesh, A.; Khilart, C. (1995). Kartic. Influence of mineral matter on biomass pyrolysis characteristics. Fuel, 12: 1812-1822.

Rhmann, W.; Pandey, B.; Ansari, G. and Pandey, D.K. (2019). Software fault prediction based on change materics using hybrid algorithms: An empirical study. Jour. of King Saud Univ.Comp. and Inform. Scien. Xxx-xxx.

Rhmann, W.; Pandey, B.; Ansari, G. and Pandey, D.K. (2019). Software fault prediction based on change materics using hybrid algorithms: An empirical study. Jour. of King Saud Univ.Comp. and Inform. Scien. Xxx-xxx.

Saini, G.; Khamparia, A. and Luhach, A. (2019). Classification of Plants Using Convolutional Neural Network. First_Intern._Conf._on_Sust._Technol._for Comp._Intellig. 551-561.

Saini, G.; Khamparia, A. and Luhach, A. (2019). Classification of Plants Using Convolutional Neural Network. First_Intern._Conf._on_Sust._Technol._for Comp._Intellig. 551-561.

Sethi, N.; Agrawal, P.; Madaan, V.; Singh, S.K. and Kumar, A. (2016). Automated title generation in enlish language using NLP. I J C T A, 9(11): 5159-5168.

Sethi, N.; Agrawal, P.; Madaan, V.; Singh, S.K. and Kumar, A. (2016). Automated title generation in enlish language using NLP. IJCTA, 9(11): 5159-5168.

Singh, R.; Thakur, K.;_Singh, G. and Gupta, S. (2019). Prevention of IP spoofing attack in cyber using artificial Bee colony and artificial neural network. Third Intern. Conf.; 10.1145/3339311.3339327.

Singh, R.; Thakur, K.; Singh, G. and Gupta, S. (2019). Prevention of IP spoofing attack in cyber using artificial Bee colony and artificial neural network. Third Intern. Conf.; 10.1145/3339311.3339327.

Takkar, S.; Singh, A. and Pandey, B. (2017). Application of machine learning algorithms to a well defined clinical problem: Liver disease. Intern. Jour. of E-Heal. and Medic. Commun.; 8(4): 1-23.

Takkar, S.; Singh, A. and Pandey, B. (2017). Application of machine learning algorithms to a well defined clinical problem: Liver disease. Intern. Jour. of E-Heal. and Medic. Commun.; 8(4): 1-23.

Takyi, K.; Bagga, A. and Gupta, P. (2019). A Semi-Supervised QoS-Aware Classification for Wide Area Networks with Limited Resources. Intern. Jour. of Innov. Technol. and Explor. Eng. (IJITEE) ISSN: 2278-3075, V8(11).

Takyi, K.; Bagga, A. and Gupta, P. (2019). A Semi-Supervised QoS-Aware Classification for Wide Area Networks with Limited Resources. Intern. Jour. of Innov. Technol. and Explor. Eng. (IJITEE) ISSN: 2278-3075, V8(11).

Tuya, B.; Abdelkar, C.; Manuel, G.P.; Denis, R.; Christian, R. (2004). Colloidal properties of bio-oils obtained by vacuum pyrolysis of softwood bark, Characterization of water-soluble and water-insoluble fractions. Journal of Energy and Fuel, 18(3): 704–12.

Velden, M.V.; Baeyens, J.; Boukis, I. (2007). Operating Parameters for the Circulating Fluidized Bed (CFB) Pyrolysis of Biomass. Proceedings of European Congress of Chemical Engineering (ECCE-6) Copenhagen, 16-20.

Wang, X.; Kersten, S.R.A.; Prins, W.; W.S. Van, W.S. (2005). Biomass pyrolysis in a fluidized bed reactor. Part 2: Experimental Validation of Model Results, Journal of Industrial Engineering Chemistry. Res. 44(23): 8786-8795.

Yang, H.; Yan, R.; Chen, H.; Lee, D.H., Zheng, C. (2007).Characteristics of hemicellulose, cellulose and lignin pyrolysis. Fuel, 86: 1781–1788.