

Sarcasm Detection in Headline News using Machine and Deep Learning Algorithms

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Abstract: Sarcasm is commonly used in news and detecting sarcasm in headline news is challenging for humans and thus for computers. The media regularly seem to engage sarcasm in their news headline to get the attention of people. However, people find it tough to detect the sarcasm in the headline news, hence receiving a mistaken idea about that specific news and additionally spreading it to their friends, colleagues, etc. Consequently, an intelligent system that is able to distinguish between can sarcasm none sarcasm automatically is very important. The aim of the study is to build a sarcasm model that detect headline news using machine and deep learning and attempt to understand how a computer learns the patterns of sarcasm. The dataset used in this study was collected from Kaggle depository. We examined 21 algorithms of machine learning and one deep learning algorithm for detecting sarcasm in headline news. The evaluation metric used in this study are Accuracy, F1-measure, Recall, Precision, and Time needed for training and evaluation. The deep learning model achieved accuracy (95.27%), recall (96.62%), precision (94.15%), F1-score (95.37%) and time needed to train the mode (400 seconds), with loss of around 0.3398. However, the algorithm of machine learning that achieved the highest F1-Score is Passive Aggressive Classifier. It was the top classier for sarcasm detection among the machine learning algorithms with accuracy (95.50%), recall (96.09 %), precision (94.30%), F1-score (95.19%) and time needed to train the mode (0.31 seconds).

Keywords: Machine Learning, Deep Learning, Sarcasm Detection, Natural Language Processing, Word Embedding

1. Introduction

The progression in communication technologies has a substantial effect on our day-to-day lives. The increase of social media platforms has provided a good source of data for researchers across numerous fields similar to computer vision, natural language processing, speech and signal processing, and far more. When it comes to opinion and emotions of the people towards any topic or service, evaluation of the accurate sentiment is of the spirit because unfair or incorrectly recognized comment may lead to vagueness for users plus for the system itself. Existing systems have limited capability for recognition of metaphorical language. Thus making the problem further interesting and appropriate to be studied precisely for the areas like social sciences, news headlines, online markets because people tend to be more imaginative while using sarcasm and oral irony for stating their emotion and opinions.

Machine Learning (ML) is an area of Artificial Intelligence (AI) [1-10]. Machine learning's overall objective is to evaluate data structure and fit it into models that people can comprehend and use [1-15]. In machine learning, tasks are divided into two types: supervised and unsupervised [15-20]. These classifications are based on how learning is received or how the system receives feedback on learning [21-25].

A computer may use data to create a mathematical model that learns to make predictions using machine learning [26-30]. Simply said, machine learning provides general-purpose mathematical frameworks that approximate the distribution of data rather than creating a mathematical equation or theory that precisely specifies how a system operates [31-35]. Machine learning is the study of creating programs that, rather than following a set of instructions, improve their performance over time by gaining experience from previously collected data [35-40]. Machine learning is a broad term that includes a variety of topics and domains that work together to make learning feasible [41-45]. Computer science, statistics, and probability theory are the most significant of them [45-50]. These topics can be used to tackle challenges that have become more important in modern society as more and more data is gathered and stored in a variety of sectors [51-55]. The broad diversity of application fields that have emerged since its beginnings has been one of the most demanding and fascinating aspects of machine learning: astronomy, oil and gas exploration, web-user activity analysis, page ranking, collaborative filtering, translation, and so on [55-60].

Deep Learning (DL) is a nebulous word that has had numerous distinct interpretations throughout the years [61-65]. It is described as the breakdown of complicated notions into basic concepts and the recombination of simple concepts into new complex concepts there [66-70]. As a result, an algorithm must build a hierarchy of ideas. A multi-layered graph, referred to as "deep" in graph theory, would be a visual representation of this structure [71-80].

Previous studies in Sarcasm detection typically make use of Twitter datasets collected using hashtag based supervision but such datasets are noisy in terms of labels and language. Furthermore, many tweets are replies to other tweets and detecting sarcasm in these requires the availability of contextual tweets. To overcome these limitations related to noise in Twitter datasets, this News Headlines dataset for Sarcasm Detection was collected from two news website. TheOnion aims at producing sarcastic versions of current events and all the headlines were collected from News in Brief and News in Photos categories (which are sarcastic). Real (and non-sarcastic) news headlines were collected from HuffPost.

This new dataset has the following advantages over the existing Twitter datasets:

- Since news headlines are written by professionals in a formal manner, there are no spelling mistakes and informal usage. This reduces the sparsity and also increases the chance of finding pre-trained embeddings.
- Furthermore, since the sole purpose of TheOnion is to publish sarcastic news, we get high-quality labels with much less noise as compared to Twitter datasets.
- Unlike tweets which are replies to other tweets, the news headlines we obtained are self-contained. This would help us in teasing apart the real sarcastic elements.

Each record in the dataset consists of three attributes:

- `is_sarcastic`: 1 if the record is sarcastic otherwise 0.
- `headline`: the headline of the news article.
- `article_link`: link to the original news article. Useful in collecting supplementary data.

This new Dataset can be found in Kaggle depository. It consists of 28618 records as a json files[87].

2. Literature Review

Sarcasm detection is a task that has been explored, but not widely. Previously, researchers have built sarcasm detectors using neural networks and/or other classifiers on datasets like tweets [84] and Flickr images [81]. Some researchers focus more on sentiment analysis and tie it to sarcasm detection. Poria et al., used deep convolutional neural networks and features extraction using pre-trained sentiment, emotion and personality models. Das and Clark built a convolutional neural network-based model utilizing the captions and visual contents of images to predict sarcasm.

Most research centered on sarcasm detection was assisted by sentiment or emotion data. Maynard and Greenwood [83] investigated the use of sarcasm in tweets and their effect on sentiment analysis which suggests that when sarcasm is identified accurately, it can improve sentiment analysis by almost 50%. However, the accuracy of their program was still low even though the tweet was identified as sarcastic or non-sarcastic correctly. Over time, researchers have developed a variety of methods in the sarcasm detection.

Recently, Devlin et al. developed BERT, a system of bidirectional transformers that encodes sequence of words into constant-length vectors [82]. BERT is pre-trained on a variety of tasks and excels at masked prediction, question answering, and sentiment classification, among others, they achieved 92%.

Another solution which exists was developed by Mandal and Mahto [86] achieved an accuracy of 86.16%. This detector was built using Deep CNN-LSTM with word embeddings. A similar problem statement was solved by Ahuja, Bansal, Prakash, Venkataraman and Banga [85]. Their solution includes the use of 12 classification algorithms using split ratios of 50:50, 25:75 and 90:10. Out of these 12 algorithms, gradient boosting resulted in the best accuracies.

As mentioned above, majority of the previous solutions use Twitter datasets but these datasets are noisy when considered with respect to their labels and language. Our dataset which consists of news headlines was collected from Kaggle repository[87] has the following advantages over the previously used Twitter dataset. First, news headlines are written by journalists in a very formal way and therefor guarantee the minimum of spelling mistakes, which makes this task somewhat easier as it reduces the scatteredness and also increases the chances of finding pre-trained embeddings. Furthermore, since the sole purpose of TheOnion is to publish sarcastic news, we got high-quality labels with much less noise as compared to Twitter datasets. Unlike tweets which are replies to other tweets, the news headlines we obtained are self-contained. This would help us in teasing apart the real sarcastic elements. The content of each record consists of three attributes:(`is_sarcastic`, `headline` `article_link`).

3. Exploratory Data Analysis

The dataset comes in a json format, which when processed can be read as a pandas data frame, having 28618 headlines and one column name referring to the article link of the headline, the headline itself, and whether the headline was intended to be sarcastic or not.

The target is to train a group machine-learning and deep learning algorithms and choose the best one among them so that it can predict whether or not a news headline is sarcastic in the upcoming news headlines.

Since we do not need the article link, we dropped it from the dataset. Furthermore, there are no null values and thus the data is complete.

The dataset is characterized into two categories, which are labelled 0 if the headline is non-sarcastic and 1 if the headline is sarcastic as can be seen in Figure 1.

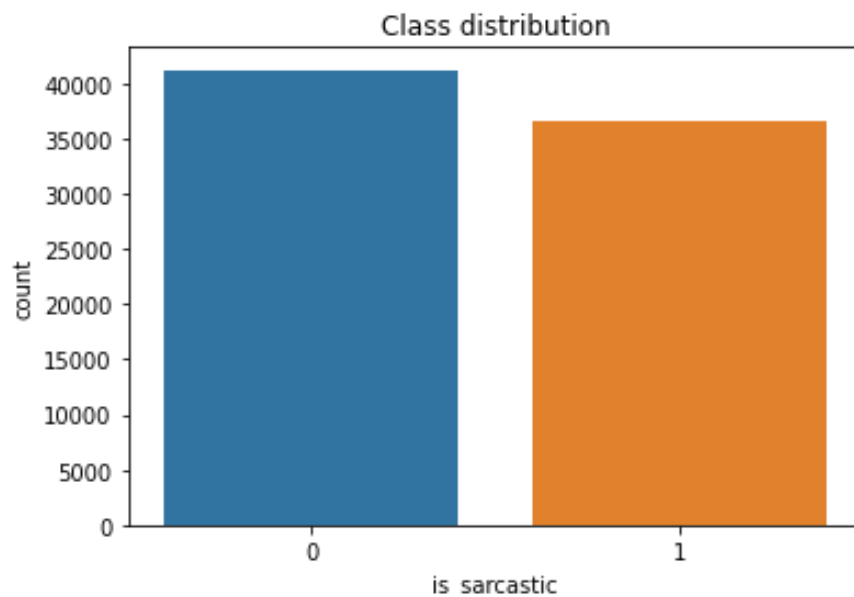


Figure 1: Is_sarcastic class distribution

The mean of this data column is almost 0.44. That indicate that the dataset is not severely skewed and therefore is appropriate for our study.

Additionally, all the sarcastic headlines come from The Onion and none sarcastic from HuffPost.

We then tokenized (a feature of the Keras framework of Python) all the headlines and made a dictionary. We then proceed to carry out our study by using the main concept of applying a LSTM over the processed embedded sentences (news headlines) and other machine learning algorithms: Extra Trees Classifier, Passive Aggressive Classifier, RidgeClassifier, Perceptron, XGBClassifier, Nearest Centroid, MultinomialNB, Linear SVC, Extra Tree Classifier, SGDClassifier, Calibrated Classifier CV, ComplementNB, BernoulliNB, Bagging Classifier, LGBM Classifier, AdaBoost Classifier, KNeighbors Classifier, Logistic Regression, Gradient Boosting Classifier, Decision Tree Classifier, MLPClassifier for sarcastic detection.

4. Proposed Machine and Deep Learning Models

The overall models are supervised learning models which after modifying the raw dataset consists of headlines, a corresponding label of whether that headline was sarcastic or not, and we added a new column called length which gives the length of the headlines, as the starting data before any of it is fed to any of the proposed models. Figure 2 shows the frequency of the length of each

headline in the dataset.

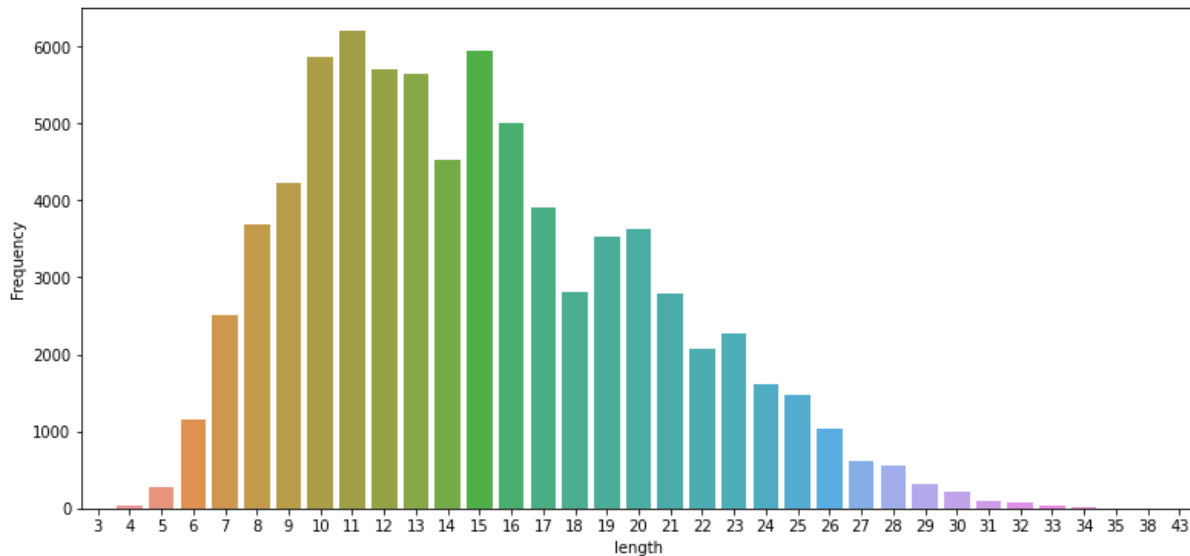


Figure 2 the frequency of the length of each headline in the dataset.

4.1 The methodology used in our study was as follows:

1. The first step was to go over every headline and create from it two new headlines using the function `aug_bert.augment`. Thus, we have three times the number of headlines (i.e. we have 85,854 headline news). Then we saved it as csv file for next step.
2. The second step was to study the length of each headline and discard the shortest and longest headlines. We decide to discard the headlines that is less than 45 characters and the headlines that are greater than 180 characters.
3. The third step was to replace the short phrases with complete phrases like “won’t” to be “will not”.

4.1.1 For Deep learning algorithm, we continued with the following steps:

5. The fourth step was to use the **Tokenizer** feature/framework from Keras. This feature basically allowed the initial sentences to be converted to a more suitable form where each headline is converted to sequence of maximum 300 words. The extra spaces after the headline ended would be padded.
6. The fifth step is the preparation of the Embedding Matrix. It is a matrix with vectors having the word embeddings for each of the unique words selected by the tokenizer in step four. The embedding matrix was constructed using pre-trained word embeddings from the GloVe word embeddings by Stanford. From this 'txt' file with each line consisting of a word and its corresponding word embedding. The shape of the embedding matrix thus constructed turned out to be [38348, 300], as per NumPy shape types.
7. The sixth step was building the deep learning model. The model architecture started with taking the initial tokenized headline, and through the embedding matrix, giving the features for each word in a sequence. Then the output is passed through the LSTM. Then passed to two dense layers of sizes (128, and 64 units). Then the output layer with one unit as we have two categories. A standard “binary_crossentropy” loss is used, alongside an 'Adam' optimizer, which are usual first choices in such cases. An accuracy metric was chosen to keep track of performance. The deep learning model architecture is shown in Figure 3.

```

Model: "model"
-----
Layer (type)                Output Shape                Param #
-----
input (InputLayer)          [(None, 20)]                0
embedding (Embedding)       (None, 20, 300)            11504400
lstm (LSTM)                  (None, 256)                 570368
flatten (Flatten)           (None, 256)                 0
dense (Dense)                (None, 128)                 32896
dense_1 (Dense)             (None, 64)                  8256
output (Dense)              (None, 1)                   65
-----
Total params: 12,115,985
Trainable params: 611,585
Non-trainable params: 11,504,400
    
```

Figure 3: Deep learning model architecture

4.1.2 For the machine learning algorithms, we continued with the following steps:

4. The fourth step was to use feature extraction by TfidfVectorizer from sklearn.
5. The fifth step to use fit_transform with training and testing datasets.
6. The sixth step to use each proposed machine leaning algorithm and record its performance.

5. Performance Evaluation

We have split the dataset into three datasets (training, testing, and validation datasets). The ratio of splitting was 60% for training and 20% for each of the testing and validation datasets.

After training and cross validating the model, we have tested each model of the deep learning and the machine learning algorithms.

The deep learning model achieved recall (96.62%), precision (94.15%), F1-score (95.37%) and time needed to train the mode (400 seconds), with loss of around 0.3398. However, the algorithm of machine learning that achieved the highest F1-Score is Passive Aggressive Classifier. It was the top classier for sarcasm detection with recall (96.09 %), precision (94.30%), F1-score (95.19%) and time needed to train the mode (0.31 seconds). Table 1 outlines the performance of each model.

Table 1: Performance of each model

Model Name	Accuracy	Precision	Recall	F1_score	Time in seconds
ExtraTreesClassifier	93.92%	95.64%	91.25%	93.40%	1353
PassiveAggressiveClassifier	95.50%	96.09%	94.30%	95.19%	0.31
RidgeClassifier	93.64%	94.64%	91.69%	93.14%	1.04
XGBClassifier	72.04%	69.30%	72.95%	71.08%	116.05
Perceptron	94.64%	94.98%	93.57%	94.27%	0.27
NearestCentroid	76.97%	73.24%	85.24%	76.71%	0.16

MultinomialNB	92.49%	97.33%	86.43%	91.56%	0.20
LinearSVC	94.59%	95.46%	92.93%	94.18%	0.82
ExtraTreeClassifier	78.77%	77.12%	78.09%	77.60%	12.73
SGDClassifier	85.09%	85.56%	82.21%	83.85%	0.22
CalibratedClassifierCV	93.88%	94.66%	92.22%	93.42%	3.37
ComplementNB	93.62%	96.40%	89.80%	92.98%	0.21
BernoulliNB	92.36%	99.25%	84.42%	91.24%	0.31
BaggingClassifier	80.94%	86.93%	70.58%	77.59%	2011.58
LGBMClassifier	78.75%	79.54%	73.88%	76.61%	24.07
AdaBoostClassifier	72.32%	69.94%	72.30%	71.10%	43.05
KNeighborsClassifier	84.18%	86.55%	78.62%	82.40%	34.88
LogisticRegression	87.28%	88.39%	84.04%	86.16%	15.77
GradientBoostingClassifier	72.56%	69.86%	73.41%	71.59%	228.45
DecisionTreeClassifier	79.11%	81.22%	72.36%	76.54%	293.14
MLPClassifier	94.65%	95.38%	93.16%	94.25%	646.37
Proposed Deep Learning model	95.27%	94.15%	96.62%	95.37%	400.00

The accuracy achieved by the sarcasm detector built by Mandal and Mahto was 86.16%. This detector was built using Deep CNN-LSTM with word embeddings and was used to detect sarcasm in news headlines. The paper written by Ahuja Bansal Prakash Venkataraman and Banga include the deployment of 12 classification algorithms using split ratios of 50:50 25:75 and 90:10. In all the three cases the gradient boosting algorithm gave the best accuracies i.e. 85.14% 85.71% and 85.03% on the three respective split cases. Note: The three models need not necessarily be trained and tested on the same dataset.

We calculated the Accuracy, Precision, Recall and F1-Score metrics using the following formulas:

$$ACC = \frac{TP+TN}{TP+TN+FP+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} = \frac{2TP}{2TP+FP+FN}$$

6. Conclusion

In our study, we were able to correctly detect the sarcasm found in various headlines around the world. We were able to correctly classify the headlines based on used words with an accuracy of 95.37% using machine and deep learning algorithms. We were also able to make the predictions of the sarcasm present in particular news headline. We can see that our LSTM along with the GloVe embeddings performed exceptionally well on our dataset. Our deep learning model and machine learning models were capable of learning to distinguish between sarcastic and non-sarcastic headlines with no context a task which many humans have difficulty with.

References

1. Abu Nada, A. M., et al. (2020). "Age and Gender Prediction and Validation through Single User Images Using CNN." International Journal of Academic Engineering Research (IJAER) 4(8): 21-24.
2. Abu Nada, A. M., et al. (2020). "Arabic Text Summarization Using AraBERT Model Using Extractive Text Summarization Approach." International Journal of Academic Information Systems Research (IJAISR) 4(8): 6-9.
3. Abu-Jamie, T. N., et al. (2022). "Six Fruits Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 6(1): 1-8.
4. Abu-Saqer, M. M., et al. (2020). "Type of Grapefruit Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 4(1): 1-5.
5. Afana, M., et al. (2018). "Artificial Neural Network for Forecasting Car Mileage per Gallon in the City." International Journal of Advanced Science and Technology 124: 51-59.
6. Aish, M. A., et al. (2022). "Classification of pepper Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 6(1): 24-31.
7. Al Barsh, Y. I., et al. (2020). "MPG Prediction Using Artificial Neural Network." International Journal of Academic Information Systems Research (IJAISR) 4(11): 7-16.
8. Alajrami, E., et al. (2019). "Blood Donation Prediction using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 3(10): 1-7.
9. Alajrami, E., et al. (2020). "Handwritten Signature Verification using Deep Learning." International Journal of Academic Multidisciplinary Research (IJAMR) 3(12): 39-44.
10. Al-Araj, R. S. A., et al. (2020). "Classification of Animal Species Using Neural Network." International Journal of Academic Engineering Research (IJAER) 4(10): 23-31.
11. Al-Araj, R. S. A., et al. (2020). "Classification of Animal Species Using Neural Network." International Journal of Academic Engineering Research (IJAER) 4(10): 23-31.
12. Al-Atrash, Y. E., et al. (2020). "Modeling Cognitive Development of the Balance Scale Task Using ANN." International Journal of Academic Information Systems Research (IJAISR) 4(9): 74-81.
13. Al-Atrash, Y. E., et al. (2020). "Modeling Cognitive Development of the Balance Scale Task Using ANN." International Journal of Academic Information Systems Research (IJAISR) 4(9): 74-81.
14. Alfarrar, A. H., et al. (2022). "Classification of Pineapple Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 5(12): 37-41.
15. Alghoul, A., et al. (2018). "Email Classification Using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 2(11): 8-14.
16. Alghoul, A., et al. (2018). "Email Classification Using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 2(11): 8-14.
17. Alkahlout, M. A., et al. (2022). "Classification of Fruits Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 5(12): 56-63.
18. Al-Kahlout, M. M., et al. (2020). "Neural Network Approach to Predict Forest Fires using Meteorological Data." International Journal of Academic Engineering Research (IJAER) 4(9): 68-72.
19. Alkronz, E. S., et al. (2019). "Prediction of Whether Mushroom is Edible or Poisonous Using Back-propagation Neural Network." International Journal of Academic and Applied Research (IJAAAR) 3(2): 1-8.
20. Almadhoun, H. et al. (2021). "Classification of Alzheimer's Disease Using Traditional Classifiers with Pre-Trained CNN." International Journal of Academic Health and Medical Research (IJAHMR) 5(4): 17-21.
21. Almadhoun, H. R., et al. (2022). "Detection of Brain Tumor Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 6(3).
22. Al-Madhoun, O. S. E.-D., et al. (2020). "Low Birth Weight Prediction Using JNN." International Journal of Academic Health and Medical Research (IJAHMR) 4(11): 8-14.
23. Al-Masawbe, M. M. et al. (2022). "Papaya maturity Classification Using Deep Convolutional Neural Networks." International Journal of Engineering and Information Systems (IJEIS) 5(12): 60-67.
24. Al-Massri, R., et al. (2018). "Classification Prediction of SBRCTs Cancers Using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 2(11): 1-7.
25. Al-Mobayyed, A. A., et al. (2020). "Artificial Neural Network for Predicting Car Performance Using JNN." International Journal of Engineering and Information Systems (IJEIS) 4(9): 139-145.
26. Al-Mubayyed, O. M., et al. (2019). "Predicting Overall Car Performance Using Artificial Neural Network." International Journal of Academic and Applied Research (IJAAAR) 3(1): 1-5.
27. Alsaaqqa, A. H., et al. (2022). "Using Deep Learning to Classify Different types of Vitamin." International Journal of Academic Engineering Research (IJAER) 6(1): 1-6.
28. Alshawwa, I. A., et al. (2020). "Analyzing Types of Cherry Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 4(1): 1-5.
29. Al-Shawwa, M., et al. (2018). "Predicting Temperature and Humidity in the Surrounding Environment Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(9): 1-6.
30. Ashqar, B. A., et al. (2019). "Plant Seedlings Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 3(1): 7-14.
31. Bakr, M. A. H. A., et al. (2020). "Breast Cancer Prediction using JNN." International Journal of Academic Information Systems Research (IJAISR) 4(10): 1-8.
32. Barhoom, A. M., et al. (2019). "Predicting Titanic Survivors using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 3(9): 8-12.
33. Barhoom, A. M., et al. (2022). "Diagnosis of Pneumonia Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 6(2).
34. Belbeisi, H. Z., et al. (2020). "Effect of Oxygen Consumption of Thylakoid Membranes (Chloroplasts) From Spinach after Inhibition Using JNN." International Journal of Academic Health and Medical Research (IJAHMR) 4(11): 1-7.
35. Dalffa, M. A., et al. (2019). "Tic-Tac-Toe Learning Using Artificial Neural Networks." International Journal of Engineering and Information Systems (IJEIS) 3(2): 9-19.
36. Dawood, K. J., et al. (2020). "Artificial Neural Network for Mushroom Prediction." International Journal of Academic Information Systems Research (IJAISR) 4(10): 9-17.
37. Dheir, I. M., et al. (2020). "Classifying Nuts Types Using Convolutional Neural Network." International Journal of Academic Information Systems Research (IJAISR) 3(12): 12-18.
38. Dheir, I. M., et al. (2022). "Classification of Anomalies in Gastrointestinal Tract Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 6(3).
39. El-Habil, B., et al. (2022). "Cantaloupe Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 5(12): 7-17.
40. El-Khatib, M. J., et al. (2019). "Glass Classification Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 3(2): 25-31.
41. El-Mahelawi, J. K., et al. (2020). "Tumor Classification Using Artificial Neural Networks." International Journal of Academic Engineering Research (IJAER) 4(11): 8-15.
42. El-Mashharawi, H. Q., et al. (2020). "Grape Type Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 3(12): 41-45.
43. Elsharif, A. A. E. F., et al. (2022). "Retina Diseases Diagnosis Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 6(2).
44. Elzamy, A., et al. (2015). "Classification of Software Risks with Discriminant Analysis Techniques in Software planning Development Process." International Journal of Advanced Science and Technology 81: 35-48.
45. Elzamy, A., et al. (2015). "Predicting Software Analysis Process Risks Using Linear Stepwise Discriminant Analysis: Statistical Methods." Int. J. Adv. Inf. Sci. Technol 38(38): 108-115.
46. Elzamy, A., et al. (2017). "Predicting Critical Cloud Computing Security Issues using Artificial Neural Network (ANNs) Algorithms in Banking Organizations." International Journal of Information Technology and Electrical Engineering 6(2): 40-45.
47. Habib, N. S., et al. (2020). "Presence of Amphibian Species Prediction Using Features Obtained from GIS and Satellite Images." International Journal of Academic and Applied Research (IJAAAR) 4(11): 13-22.
48. Harz, H. H., et al. (2020). "Artificial Neural Network for Predicting Diabetes Using JNN." International Journal of Academic Engineering Research (IJAER) 4(10): 14-22.
49. Hassanein, R. A. A., et al. (2020). "Artificial Neural Network for Predicting Workplace Absenteeism." International Journal of Academic Engineering Research (IJAER) 4(9): 62-67.
50. Heriz, H. H., et al. (2018). "English Alphabet Prediction Using Artificial Neural Networks." International Journal of Academic Pedagogical Research (IJAPR) 2(11): 8-14.
51. Jaber, A. S., et al. (2020). "Evolving Efficient Classification Patterns in Lymphography Using EasyNN." International Journal of Academic Information Systems Research (IJAISR) 4(9): 66-73.
52. Khashf, D. W. A., et al. (2018). "Predicting DNA Lung Cancer using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(10): 6-13.
53. Khalil, A. J., et al. (2019). "Energy Efficiency Predicting using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 3(9): 1-8.
54. Khalil, A. J., et al. (2022). "Diagnosis of Blood Cells Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 6(2).
55. Kweik, O. M. A., et al. (2020). "Artificial Neural Network for Lung Cancer Detection." International Journal of Academic Engineering Research (IJAER) 4(11): 1-7.
56. Maghari, A. M., et al. (2020). "Books' Rating Prediction Using Just Neural Network." International Journal of Engineering and Information Systems (IJEIS) 4(10): 17-22.
57. Alnajjar, M. K., et al. (2022). "Heart Sounds Analysis and Classification for Cardiovascular Diseases Diagnosis using Deep Learning." International Journal of Academic Engineering Research (IJAER) 6(1): 7-23.
58. Megdad, M. M., et al. (2022). "Fraudulent Financial Transactions Detection Using Machine Learning." International Journal of Academic Information Systems Research (IJAISR) 6(3).
59. Mettleq, A. S. A., et al. (2020). "Mango Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 3(12): 22-29.
60. Metwally, N. F., et al. (2018). "Diagnosis of Hepatitis Virus Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(11): 1-7.
61. Mohammed, G. R., et al. (2020). "Predicting the Age of Abalone from Physical Measurements Using Artificial Neural Network." International Journal of Academic and Applied Research (IJAAAR) 4(11): 7-12.
62. Musleh, M. M., et al. (2019). "Predicting Liver Patients using Artificial Neural Network." International Journal of Academic Information Systems Research (IJAISR) 3(10): 1-11.
63. Obaid, T., et al. (2022). Factors Contributing to an Effective E-Government Adoption in Palestine. International Conference of Reliable Information and Communication Technology, Springer, Cham.
64. Oriban, A. J. A., et al. (2020). "Antibiotic Susceptibility Prediction Using JNN." International Journal of Academic Information Systems Research (IJAISR) 4(11): 1-6.
65. Qwaider, S. R., et al. (2020). "Artificial Neural Network Prediction of the Academic Warning of Students in the Faculty of Engineering and Information Technology in Al-Azhar University-Gaza." International Journal of Academic Information Systems Research (IJAISR) 4(8): 16-22.
66. Sadek, R. M., et al. (2019). "Parkinson's Disease Prediction Using Artificial Neural Network." International Journal of Academic Health and Medical Research (IJAHMR) 3(1): 1-8.
67. Salah, M., et al. (2018). "Predicting Medical Expenses Using Artificial Neural Network." International Journal of Engineering and Information Systems (IJEIS) 2(20): 11-17.
68. Saleh, A. et al. (2020). "Brain Tumor Classification Using Deep Learning." 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech). IEEE, 2020.
69. Salman, F. M., et al. (2020). "COVID-19 Detection using Artificial Intelligence." International Journal of Academic Engineering Research (IJAER) 4(3): 18-25.
70. Salman, F. M., et al. (2022). "Classification of Real and Fake Human Faces Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 6(3).
71. Samhan, L. F., et al. (2022). "Classification of Alzheimer's Disease Using Convolutional Neural Networks." International Journal of Academic Information Systems Research (IJAISR) 6(3).
72. Samra, M. N. A., et al. (2020). "ANN Model for Predicting Protein Localization Sites in Cells." International Journal of Academic and Applied Research (IJAAAR) 4(9): 43-50.
73. Shawarib, M. Z. A., et al. (2020). "Breast Cancer Diagnosis and Survival Prediction Using JNN." International Journal of Engineering and Information Systems (IJEIS) 4(10): 23-30.
74. Zaouq, I., et al. (2015). "Predicting Student Performance Using Artificial Neural Network: in the Faculty of Engineering and Information Technology." International Journal of Hybrid Information Technology 8(2): 221-228.
75. Aldammagh, Z., Abdeljawad, R., & Obaid, T. (2021). Predicting Mobile Banking Adoption: An Integration of TAM and TPB with Trust and Perceived Risk. Financial Internet Quarterly, 17(3), 35-46.
76. Obaid, T. (2021). Predicting Mobile Banking Adoption: An Integration of TAM and TPB with Trust and Perceived Risk. Available at SSRN 3761669.
77. Jouha, H., Abu Jarad, A., Obaid, T., Abu Mdallalah, S., & Awaja, A. (2020). Mobile Banking Adoption: Decomposed Theory of Planned Behavior with Perceived Trust. Available at SSRN 3660403.
78. Obaid, T., Abdeljawad, R., & Mdallalah, S. A. (2020). Factors Driving E-Learning Adoption In Palestine: An Integration of Technology Acceptance Model And IS Success Model. Available at SSRN 3686490.
79. Obaid, T. F., & Eneizan, B. M. (2016). Transfer of training and post-training on job performance in Middle Eastern countries. Review of Public Administration and Management, 400(3786), 1-11.
80. Obaid, T. F., Zainon, M. S., Eneizan, P. D. B. M., & Wahab, K. A. TRANSFER OF TRAINING AND POST-TRAINING ON JOB PERFORMANCE IN MIDDLE EASTERN COUNTRIES.
81. D. Das and A. Clark "Sarcasm detection on flickr using a CNN" in International Conference on Computing and Big Data 2018.
82. J. Devlin M. Chang K. Lee and K. Toutanova "Pre-training of deep bidirectional transformers for language understanding" 2018.
83. D. Maynard and M. Greenwood "Who cares about sarcastic tweets? Investigating the impact of sarcasm on sentiment analysis" in Language Resources and Evaluation Conference (LREC) 2014.
84. S. Poria E. Cambria D. Hazarika and P. Vij "A deeper look into sarcastic tweets using deep convolutional neural networks" 2016.

85. R. Ahuja S. Bansal S. Prakash K. Venkataraman and A. Banga "Comparative Study of Different Sarcasm Detection Algorithms Based On Behavioral Approach".
86. Mandal Paul & Mahto Rakeshkumar. (2019). Deep CNN-LSTM with Word Embeddings for News Headline Sarcasm Detection.
87. kaggle.com [last access 20-3-2022]