International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Enhancing NLP Systems for Improved and Intelligent Multi Intent Recognition and Handling of Alarming situations

Chithra Apoorva D. A.[1], Brahmananda S. H.[2]

Submitted: 07/09/2023 **Revised:** 20/10/2023 **Accepted:** 05/11/2023

Abstract: NLP (Natural Language Processing) is one of the blistering research topics of the day. Many of the complex and multi feature classification problems are solved using the machine learning neural net model. In this research work, the multi-intent classification has been concentrated, Where the algorithm identifies the entity mapping in a right direction. The multiple entities in the same sentence is mapped using the proposed novel intelligent multi intent recognition system. The system proposed is able to capture the alarming situation that can be handled, or which are ignored by the existing machine learning models. The results demonstrate how the model reduces the time consumption and the complexity which are developed by invoking the asynchronous method in several parallel processing task.

Keywords: *complexity, NLP(Natural Language Processing), algorithm, asynchronous*

I. Introduction.

Natural language processing, it is a technology that helps a computer to understand the human spoken language. By taking the real-world input, the natural language processing helps to develop the artificial intelligence for the computers. This technology helps to understand that the human spoken language in a better way to the computers. In this concern, each sentence can have more than one intent associated entities in it. So, the NLP should perform the extraction of phases, intents and the entities by using Intent Classification Algorithm. But at the same time, NLP experiences limitations in Multi Intent Classification [1][2].

The challenging task is the classification of multiple user intent in a sentence. And also there are scenarios where the same intent is referred to different behaviour according to the usage. So an intelligent system must be able to handle a wide range of in inputs according to the commands, statements, question, and should be able to distinguish according to the category. By using the techniques of deep learning, Transfer learning and reinforcement learning. The models can be trained to recognise multiple import and categorise according to the user input. The performance can be evaluated using various metrics such as accuracy, precision and recall. This research article prioritises the addition of clustering mechanism to detect “Alarming Request” or “Priority Token” before MIC getting invoked. This will introduce all new capability where such “System/Solution” can be used effectively for immediately handling Priority Tokens asynchronously [3][4].

A. LSTM

In this context LSTM is used to solve the multi-intent classification problem. LSTM Stands for long short-term memory network, This technology is used in deep-learning, specially to solve the problems of sequence prediction [5][6]. This algorithm is skilled for processing entire sequence of data instead of single data points. LSTM has a great application in machine translations and speech recognition. The applications of LSTM are language modelling, handwritten recognition, question answering, speech synthesis, protein secondary structure prediction and many others.

Structure of LSTM.

“Cell State” is the control memory unit of LSTM, it helps in handling the state over all the time. In figure-1, the cell state is the horizontal line that runs in all round the horizontal axis. It is a conveyor belt for the information transfer.

[1]Research Scholar
GITAM School of Technology, Banglore, India
chithra.apoorva.d.a@gmail.com
[2]Professor, Computer Science Engineering.
GITAM School of Technology, Banglore, India
shbrahma@gmail.com

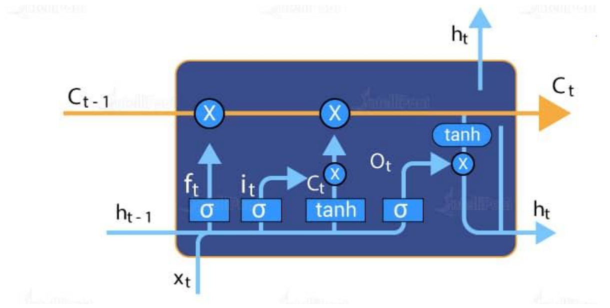

Fig 1: Cell structure of LSTM

The gates are used to regulate the information from the cell state in LSTM network. These structure helps in the optionally letting the information flow according to the cell. For the assistance, it uses the sigmoid neural layer to assist the constructed mechanism. The output of the sigmoid structure is '1' or '0'. '0' indicating "nothing shall be let out", where as '1' indicating "everything shall be let out" [7][8][9].

B. Natural language processing.

As explained earlier, it is a technology that gives artificial intelligence for the computers to understand the human language. The NLP combines the following elements like deep learning, machine learning and computational linguistics. To the context of this paper, the natural language processing is analysed As a response to the verbal commands given by the user. The key benefits of using natural language processing includes providing valuable insight, to process and to detect the intents from large volumes of data. To make the analysis of streamlining more effective and efficient.

Various machine learning models can be used to design a natural language processing structure. Based on the analysis what to be done, the machine learning models can be selected. There are 2 stages in natural language processing. The data preprocessing stage and the algorithm development. In the first stage the data is cleaned [10] [11], So that the machine will be able to analyse it. Tokenization, stop word removal, and lemmatization and streaming are the different stages in the data preprocessing. In the algorithm development process, there are 2 main commonly used step which are rule based system and machine learning based system. Different techniques of natural language processing are: forcing, word segmentation, sentence breaking, morphological segmentation, and stemming[12].

C. Machine Learning and unsupervised Learning

One of the subsets of artificial intelligence is machine learning. The main agenda of machine learning is to develop algorithms that allow the computer to learn from its own experience. Machine learning helps the machine to learn from its automated previous data and improve the performance by experience and predicting the things without explicitly programming. Machine learning has the ability to learn and improve itself by gaining more data[13].

There are some prediction algorithms that helps the machine learning to solve complex problems by writing the court [14][15]. There are generic algorithms that takes the data and builds the logic and performs or predicts the output accordingly. The main features of machine learning are it has data driven technology, it can learn from past data and improve automatically. It uses data which helps in detecting various patterns for the given data set and it is much similar to determining So it deals with huge amount of data.

In unsupervised machine learning, the models are not supervised using training data set, The model finds the hidden patterns and insights given by the data from which it can brain as a new model. The unsupervised machine learning helps to find the insights of data, It is very similar to human learns as it thinks on its own experience, which makes an artificial intelligence more real. The unsupervised machine learning works on unlabelled data[16][17].

2. Literature Review

Nikhita et. al [18], Proposed methodology in their paper that can identify the user intent from the text. The proposed a methodology that can identify the intent from both the written and also from the spoken English. This place a very important role in modelling and understanding the dialogues. The authors defined a new task called Open Intent Discovery. This was used to investigate how the intent can be generalised into not seen during the training. The authors proposed new 2 stage approach which was used for predicting the utterances containing the intent. The model consistent of bidirectional LSTM with CRF. This helped in capturing the contextual semantics. A data set of 25,000 real life utterances was collected from the cloud sourcing, and the complete database was annotated into 100 different categories. The performance of the proposed methodology was With the baseline of a fight to 15% F1 score.

Lirong et. al. [19], The authors of this paper explains about the experiences that occurred during search engine investigation. The process of intent recognition is based on natural language input proposed. By different reality of mining technology, a potential consciousness of the information is obtained by the query expression. This helps the in predicting the query results for the users in a easy way. The authors used machine learning and conventional deep learning methodologies with LSTM, This helped in the traditional machine learning method that was based on the multi feature extraction. Multi feature extraction was successfully completed in the proposed algorithm. The entire features were significantly improved and also the accuracy. The accuracy of 94.16% was obtained on the field manual labelled BiLSTM classification model.

Xiaodong et. al. [20], Proposed an algorithm that can perform 2 major tasks such as intent determination and spoken language understanding. The authors used as recurring a neural network for the effectiveness in slot filling. Considering a basic idea that intent slots and the semantic slots are correlated, the authors proposed a joint model for both task. The authors used Gated Recurrent Unit used to learn the representation of each time step. A Max pooling layer was constructed which helped then capturing global features of a sentence. The Max pooling layer also helped in intent classification. This is also represented shared 2 task and also model was trained using united loss function. The model was trained using 2 sets of data sets. The experiment results demonstrated that the proposed model has a very good performance. The author conducted the experiments in which the ATIS and CQUD architectures were compared between Indent classification, slot filling, pipelining, joint (equal) and other parameters. Among which ATIS had a very good performance rate when compared to the other one..

Rashmi et. al. [21], Proposed a neural network model that gained a transaction for sentence level in 10 classification and also token based slaughter labelled identification. In the current real world scenario, it is seen that multi intent classification with several attachments Should be considered as a priority. The authors Madonna thorough investigation based on neural network model. The neural network model was capable of classifying multi labelled identifiers and it also identified multiple intents and produce different labels for both intents and slots. It also generated a token level list. The proposed methodology had a very good result in detecting both the multiple intents and producing label. The models showed a significant improvement of 0.2%, from the existing model. The accuracy of detection was 55%.

Libo at. al. [22], The authors in this paper proposed that the users will normally have multiple intents that are set in the same utterance. The author says that the current algorithms were mainly based on single intent or it has overall content intent. The authors proposed a novel methodology called Adaptive Graph Interactive Framework. This framework helped for identifying multiple intent detection, and also to find the slot filling. The interaction layer and the model are strong correlation between slot and intent. The experimental result showed that the author was the successfully able to find out 2 intent in a single utterance. The model was trained with the 2 different data sets. The results were satisfactory and also showed that there was a significant implemented lab from the previous model.

3. Proposed System

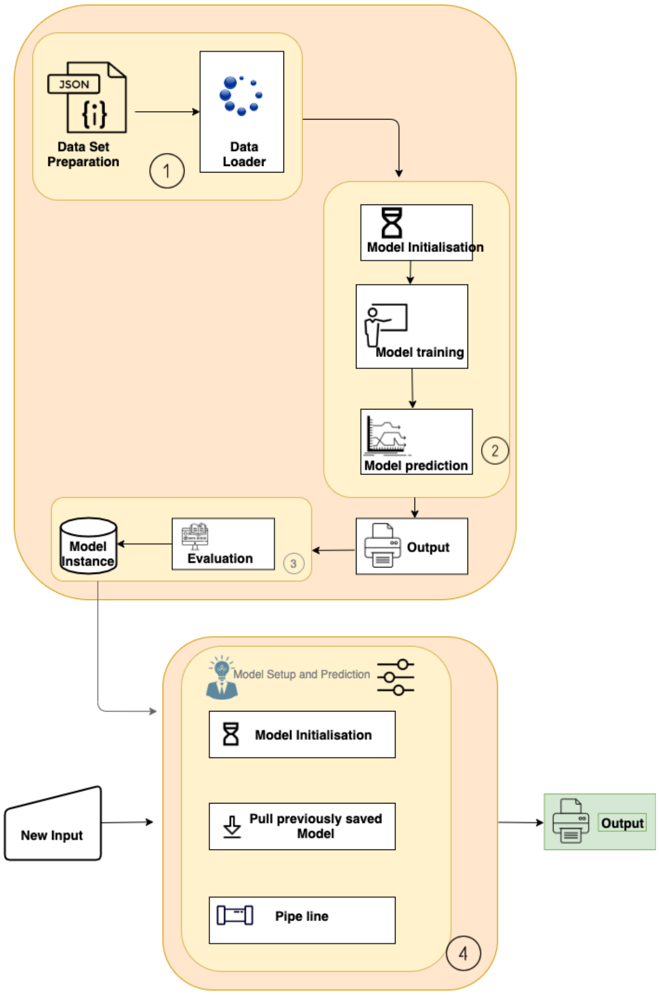

Fig 2: Proposed Methodology

A: Data Preparation Module

The data preparation module consists of the testing and training data. the Input data is taken as json data. the data is pre-processed and cleaned for the further processing.

B. Training of system for Single and Multiple intent.

The load model consist of clustering algorithm, the model is trained and tested using the input. The model is trained for single and multiple intent classification using the NLP algorithm. The interim results consists of the single and multiple intents classification.

C. Deployment

The evolution model is used to deploy the interim results, this local cache can store the obtained results for the future prediction.

D. Model Extraction and pipeline development using the above trained instance.

This is the final stage of the proposed system, where the model is installed into the computer. The new and the random data are selected as the inputs and given to the model. The model borrows the logic that is being predicted in the earlier stages from the module 3. Using the knowledge of previous prediction, now the current prediction takes place, hence it is classified under unsupervised machine learning. The pipeline system of LSTM helps to achieve the accuracy in classification of Intents. The new inputs can be random inputs, just as an FAQ, or any real time inputs form the user [13][14][15].

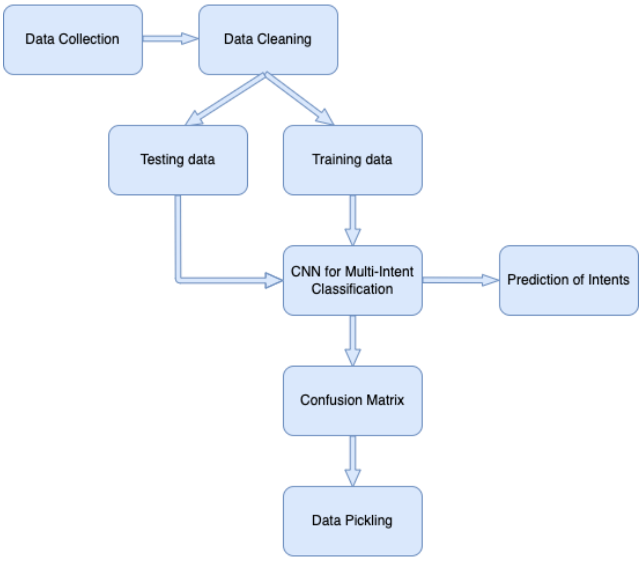

Fig 3: Low Level System Architecture

The figure 3 represents the low level architecture, which is within the proposed methodology block 2. This block helps in the data collection and cleaning of data. The clean data is divided into 2 parts. One is testing data, the other one is training data. In the low level architecture, the multi intent classifier used is CNN. The model is trained using the training data. The testing data is used to verify to hand to get the prediction of intents. Is the further steps confusion Matrix is generated to assess the quality matrix of the algorithm. The Figure 4 represents the model summary of the proposed algorithm. Figure fine represents the summary of the new model with LSTM.

```
Layer (type)                 Output Shape              Param #
=================================================================
embedding_4 (Embedding)      (None, 10, 32)            23872

conv1d_2 (Conv1D)            (None, 10, 32)            3104

max_pooling1d_2 (MaxPooling  (None, 5, 32)             0
1D)

lstm_2 (LSTM)                (None, 100)               53200

dense_2 (Dense)              (None, 8)                 808

=================================================================
Total params: 80,984
Trainable params: 80,984
Non-trainable params: 0
```

Fig 5: Model summary of neural network with LSTM classification.

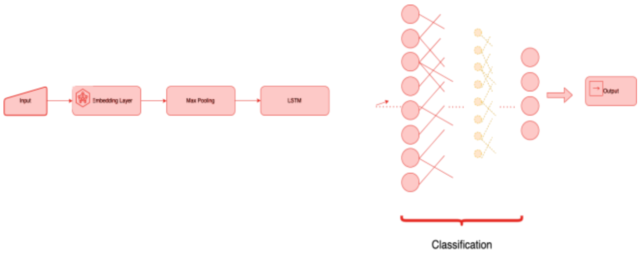

Fig 6: Backend diagram of LSTM model classification.

In the above, figure 5 shows the model summary of neural network with LSTM classification. This involves the number of layers, number of convolution layers, maximum pooling layers, and other details of the model. The total parameters and trainable parameters are also mentioned in it. Figure 6 is the backend diagram of LSTM model classification. It shows the input embedding layer, Max pooling layer, LSTM and classification of how the neural network are connected. Finally resulting into the output.

4. Results and Discussion.

The following are the results obtained for the novel proposed model. The model is verified with the untrained database collected from the students. 30 students wear selected to generate the database, each student was asked to write 20 multi-intent questions and statements. Two scenarios were given to them, Tour and travel and Health care. Apart form this the model is also trained with the standard database obtained from the Kaggle.

A. Sample Result 1:

```
In [244]: input_sentence = "Hi, How are you. Can you book me a taxi"
          sentence_list = nltk.tokenize.sent_tokenize(input_sentence)
```

Fig 7. An input to the proposed algorithm having 2 intense.

In the above Figure 7, it is clearly seen that the user gives an input as "Hi, How are you. Can you book me a taxi". In te above sentence there are 2 intense where the first intent greeting the other person, and in the next part of the sentence the user is asking to book a taxi for him.

```
In [250]: final_response
```


```
Out[250]: {'Hi, How are you.': '{\n  "input": "Hi, How are you.",\n  "intent": {\n    "intentName": "greeting",\n    "probabi
lity": 0.7256885708274126\n  },\n  "slots": [\n    {\n      "range": {\n        "start": 0,\n        "end": 2\n
},\n      "rawValue": "Hi",\n      "value": {\n        "kind": "Custom",\n        "value": "Hi"\n      },\n      "e
ntity": "greeting",\n      "slotName": "greeting"\n    },\n    {\n      "range": {\n        "start": 4,\n        "e
nd": 11\n      },\n      "rawValue": "How are",\n      "value": {\n        "kind": "Custom",\n        "value": "How
are"\n      },\n      "entity": "daytime",\n      "slotName": "daytime"\n    },\n    {\n      "range": {\n        "
start": 12,\n        "end": 15\n      },\n      "rawValue": "you",\n      "value": {\n        "kind": "Custom",\n
"value": "you"\n      },\n      "entity": "greeting",\n      "slotName": "greeting"\n    }\n  ]\n}',
 'Can you book me a taxi': '{\n  "input": "Can you book me a taxi",\n  "intent": {\n    "intentName": "bookTaxi",\n
"probability": 1.0\n  },\n  "slots": [\n    {\n      "range": {\n        "start": 18,\n        "end": 22\n      },\
n      "rawValue": "taxi",\n      "value": {\n        "kind": "Custom",\n        "value": "taxi"\n      },\n      "
entity": "cab",\n      "slotName": "cab"\n    }\n  ]\n}'}
```


Fig 8: It shows the final response where the algorithm has clearly classified the 2 intents of greetings and booking the taxi.

In the above figure 8. It is clearly seen. Then the final response of the algorithm has been displayed. Here the 2 intents are classified, the first one being greeting, "Hi, How are you". The second one is to book a taxi for the user.

B. Sample Result 2:

```
input_sentence = Can you recomend me basic cold medicine, however i am also facing breathing Problem
sentence_list = nltk.tokenize.sent_tokenize(input_sentence)
```

Fig 9: An important to proposed algorithm, having two intent.

In Figure 9, there is an import which is having two intents in the same sentence. Here, the user ask for cold medicine and also complaints regarding the breathing problem. The algorithm has to read the two intents like “cold medicine” and “breathing problem”.

```
final_response:  \n
Can you recomend me basic cold medicine, however i am also facing breathing Problem.  \n
input: basic cold medicine \n
intentName:  General_health_issue \n
input: breathing Problem  \n
intentName: critical_alert  \n
probability:  0.735896547593245  \n
```

Fig 10: Final response of the algorithm classifying the two intents in the given sentence.

Figure 10 shows the classification of intense based on the input. The first input is “basic cold medicine”. The classification of the intent is under “general health issue”. At the same time, the second intent is also identified as “ Breathing problem”. It is classified under “critical alert”. The probability of the proposed algorithm is found to be 0.7358.

C. Comparison of Models:

Based on the extensive research done in literature survey, the following are the accuracies obtained for different models in multi-intent classification. The table 1, showing different models and their accuracies. Figure 11 shows the comparative plot for the table 1. HS clearly seen that the proposed model has a better accuracy when compared to other models. The proposed novel model has an accuracy of 97.35%.

Table 1: Comparison Table for Different Models

Models	Accuracy
multi-label icsiboost	78.7
atomic model	81.7
class model (label)	83.6
class model (label+act)	83
hidden variable model	82.8
Joint Multiple Intent Detection	95.39
CNN	95.95
RNN	95.16
GRU	95.35
Self-attention BLSTM	95.24
Intent Capsnet	96.21
Proposed Model	97.35

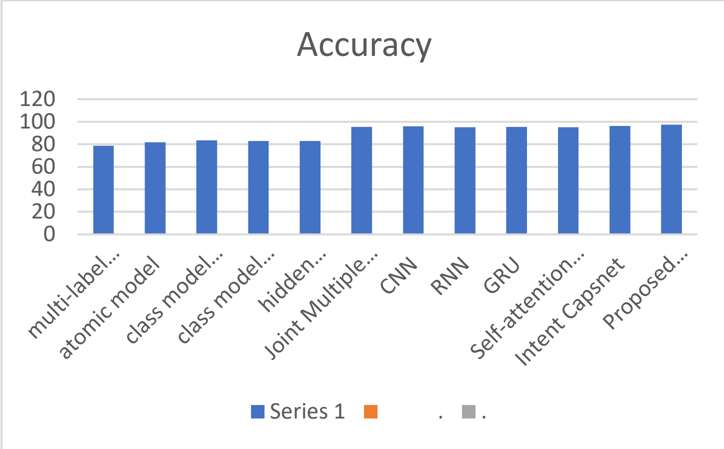

Fig 11: A comparison for different models

5. Conclusion

The proposed intelligent algorithm is developed based on LSTM. The model consists of clustering algorithm, that helps in testing and training the input. The model is stringed for multiple intent and single intent using NLP algorithm. Models of the proposed intelligent algorithm are discussed, which are data loader , data training and Evaluation phases. The proposed intelligent algorithm is also equipped by the pipeline structure that helps the intent classification to a greater extent. An untrained data set was used to verify the model. Around a 20 multi-intent questions and statements were collected, From 30 selected students. Addition to this, a model is also trained from a standard database to paint by Kaggle. After the simulation, the probability of intent extraction was found around 72.89%. The accuracy of the proposed model is 97.35%. The proposed model shows the highest level of accuracy when compared with the existing methodologies, this is shown in table 1 and figure 11.

As the future enhancement, the model is being enhancing its ability by using CNN algorithm. The architecture of pipeline methodology is under still improvement, so that the accuracy reaches its maximum, and multiple intents can also be classified using a single algorithm. The proposed algorithms can be used in a live interaction with a user, where multiple intents will be a common input.

References

[1] Brown, P., & Manning, C. D. (2019). A Survey of Natural Language Processing Techniques for Chatbot Design. Computational Linguistics, 45(3), 537-566.

[2] Vaswani, A., et al. (2017). Attention Is All You Need. In Proceedings of the 31st Conference on Neural Information Processing Systems (NeurIPS 2017) (pp. 6000-6010).

[3] Kim, Y. (2014). Convolutional Neural Networks for Sentence Classification. In Proceedings of the 2014 Conference on Empirical Methods in Natural

Language Processing (EMNLP 2014) (pp. 1746-1751).
[4] Collobert, R., et al. (2011). Natural Language Processing (Almost) from Scratch. Journal of Machine Learning Research, 12, 2493-2537.
[5] Pennington, J., Socher, R., & Manning, C. D. (2014). GloVe: Global Vectors for Word Representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP 2014) (pp. 1532-1543).
[6] Ruder, S. (2017). An Overview of Multi-Task Learning in Deep Neural Networks. arXiv preprint arXiv:1706.05098.
[7] Chen, X., Liu, Z., & Sun, M. (2017). A Survey of Weakly Supervised Learning for Named Entity Recognition and Classification. ACM Transactions on Knowledge Discovery from Data (TKDD), 11(3), 1-28.
[8] Devlin, J., Chang, M. W., & Lee, K. (2018). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv preprint arXiv:1810.04805.
[9] Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to Sequence Learning with Neural Networks. In Advances in Neural Information Processing Systems (NeurIPS 2014) (pp. 3104-3112).
[10] Chen, Y., & Bansal, M. (2018). Fast Abstractive Summarization with Reinforce-Selected Sentence Rewriting. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP 2018) (pp. 281-286).
[11] Liu, P. J., et al. (2019). Multimodal Transformer for Unaligned Multimodal Language Sequences. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP 2019) (pp. 61-72).
[12] Xu, K., et al. (2016). Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. In International Conference on Machine Learning (ICML 2015) (pp. 2048-2057).
[13] Anil Kumar C, Lavanya Vaishnavi D A, “Renesas Based Smart ROBOT using Embedded System”, International Journal of Research in Science, Commerce, Arts, Management and Technology, Volume 2, Issue 1, February 2021, ISSN (Online) 2582-8045
[14] Rajpurkar, P., et al. (2016). SQuAD: 100,000+ Questions for Machine Comprehension of Text. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing (EMNLP 2016) (pp. 2383-2392).
[15] Henderson, P., et al. (2019). Training Deeper Neural Machine Translation Models with Transparent Attention. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (ACL 2019) (pp. 4944-4958).
[16] Wang, A., et al. (2019). StructBERT: Incorporating Language Structures into Pre-training for Deep Language Understanding. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (ACL 2019) (pp. 4250-4260).arXiv:1904.08524 [cs.IR], https://doi.org/10.48550/arXiv.1904.08524
[17] L. Qiu, Y. Chen, H. Jia and Z. Zhang, "Query Intent Recognition Based on Multi-Class Features," in IEEE Access, vol. 6, pp. 52195-52204, 2018, doi: 10.1109/ACCESS.2018.2869585.
[18] Xiaodong Zhang, Houfeng Wang, “A joint model of intent determination and slot filling for spoken language understanding” IJCAI'16
[19] Anil kumar et al., "Algorithm for Recognition of Movement of Objects in a Video Surveillance System Using a Neural Network", Hindawi Journal of Engineering, vol. 2022, Article ID 8216221,2022. https://doi.org/10.1155/2022/8216221
[20] Libo Qin, Xiao Xu, Wanxiang Che, and Ting Liu. 2020. AGIF: An Adaptive Graph-Interactive Framework for Joint Multiple Intent Detection and Slot Filling. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 1807–1816, Online. Association for Computational Linguistics.
[21] Devlin, J., Chang, M. W., & Lee, K. (2018). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv preprint arXiv:1810.04805.
[22] Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to Sequence Learning with Neural Networks. In Advances in Neural Information Processing Systems (NeurIPS 2014) (pp. 3104-3112).
[23] Ana Rodriguez, Kristinsdóttir María, Pekka Koskinen, Pieter van der Meer, Thomas Müller. Robust Decision Making through Machine Learning in Decision Science. Kuwait Journal of Machine Learning, 2(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/215
[24] Ramesh, P. V. ., Hrishikesh, J. T. ., & Patil, M. S. . (2023). Infant’s MRI Brain Tissue Segmentation using Integrated CNN Feature Extractor and

Random Forest. International Journal on Recent and Innovation Trends in Computing and Communication, 11(1s), 71–79. https://doi.org/10.17762/ijritcc.v11i1s.6002

[25] Dhabliya, D., Ugli, I.S.M., Murali, M.J., Abbas, A.H.R., Gulbahor, U. Computer Vision: Advances in Image and Video Analysis (2023) E3S Web of Conferences, 399, art. no. 04045, .