JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Chatbot for Industrial Safety and Health Analytics Database using NLP and Machine learning

Ishant Kundra, Jeremy Jason Kujur, Chirag Soni
Author
Texas A&M, Manav Rachna University, University of Limerick

Ishant Kundra
Department of Computer Science and Engineering, Texas A&M University, Texas, USA

Jeremy Jason Kujur
Department of Computer Science and Engineering, Manav Rachna University, Faridabad, Haryana,India

Chirag Soni
Department of Computer Science and Engineering, University of Limerick , Limerick, Ireland

***Abstract*---**Natural Language Processing (NLP)-based chatbots have become important resources for easing human-computer communication. This research paper describes the creation and assessment of a chatbot that engages users in lively discussions using NLP approaches. The main goal of this research was to develop an effective and precise chatbot that could comprehend user inquiries and give appropriate, contextually relevant answers.
To Design a ML / CL based Chatbot utility which can help professionals to highlightthesafety risk as per the incident description. For the Data analytics, extensive Database createdfrom one of the biggest Metals & Mining Industry in Brazil which has various plants across World.

The database is basically records of accidents from 12 different plants in 03 different countries which every line in the data is an occurrence of an accident. In the high-stakes domain of industrial safety and health analysis, particularly within the intricate workings of a chemical plant, the imperative for precision, expertise, and immediate response is paramount. It is in this context that we introduce our specialized chatbot, tailored to address the unique challenges and complexities inherent to Metal and Mining plant operations. This innovative chatbot serves as a pivotal tool in ensuring the well-being of both the workforce and the surrounding environment. Its mission is twofold: to proactively identify and mitigate potential hazards, and to offer swift guidance and support in the event of an unforeseen incident. As the chemical industry continues to evolve and expand, necessitating stringent adherence to safety protocols and environmental regulations, our chatbot emerges as a dedicated and knowledgeable partner, capable of navigating the intricate landscape of chemical plant safety and health with unparalleled efficacy. In this paper, we elucidate the development, capabilities, and distinct advantages of our chatbot within this specialized context, highlighting its pivotal role in safeguarding lives, assets, and the broader community.

A dataset including accident descriptions and meta-data was used in the study. To handle textual data efficiently, NLP techniques including text preparation, tokenization, and lemmatization were used. A text-input model that exclusively used accident descriptions was created, and it was compared against a multiple-input model that included both textual and category data.
In pursuit of these objectives, this research leverages data-driven methodologies and cutting-edge technology to examine patterns, identify risk factors, and propose strategies for proactive intervention. Our aim is to contribute to the growing body of knowledge surrounding industrial safety and health, catalyzing advancements that can safeguard lives and livelihoods.
Utilising classification criteria, such as accuracy and F1-score, the models were trained and assessed. The outcomes showed that the multiple-input model beat the text-input model, obtaining a test accuracy and an F1-score on the original dataset of 73.81% and 73.81%, respectively. Additionally, learning curves and confusion matrices were used to illustrate the chatbot's performance, proving its capacity for generalisation and preventing overfitting.

The construction of the chatbot successfully demonstrates the value of NLP methods in boosting human-computer interactions. This study adds to the increasing body of knowledge in natural language processing and illustrates the promise of chatbots in a number of fields, such as customer service, information retrieval, and interactive interfaces. Future development might concentrate on enhancing the chatbot's capabilities, including new NLP tools, and improving its answer generation for more complex conversations.

Keywords: Chatbot, Natural Language Processing, NLP, Text Classification, Deep Learning, Machine Learning, Human-Computer Interaction.

Introduction : In an era marked by technological advancements and rapid industrialization, the paramount importance of safeguarding the well-being of our workforce has become increasingly evident. Industrial safety and health have emerged as pivotal concerns in contemporary society, as they not only impact the lives of countless individuals but also bear significant implications for the efficiency and sustainability of industrial operations. This paper embarks on a journey into the heart of these critical matters, shedding light on the multifaceted landscape of industrial safety and health analysis.

During the day-to-day operations, since the employee deal with harsh environment, heavy machines, unsafe work conditions safety hazards are inevitable. This raises a paramount concern to Company Management who own such industry for safety & well being of their employees.

So, it is imperative to know the reasons of safety issues to why such accidents take place affecting their employees with minor /major injuries.

The global industrial landscape is dynamic and constantly evolving, driven by innovations that promise unprecedented productivity and progress. However, this dynamism is not without its perils. The rapid pace of industrialization has given rise to a plethora of safety and health risks that demand our immediate attention. As industries push the boundaries of what is achievable, it is our ethical duty to ensure that the men and women who fuel these endeavors are shielded from harm's way.

Our research in the domain of industrial safety and health analysis for the metal and mining industry stands as a beacon of innovation in the field. With a specialized focus on this intricate sector, our work pioneers a novel approach that marries cutting-edge technology with domain- specific expertise. By training our chatbot on a dataset carefully curated from the metal and mining context, we have elevated it to a level of domain intelligence unprecedented in this area. Furthermore, our incorporation of real-time data integration and predictive analytics adds a dimension of proactiveness that has hitherto been absent. This combination of domain knowledge and advanced technology not only distinguishes our work but also has the potential to reshape safety practices within the industry. As we present our findings, it becomes evident that our research represents a truly novel contribution that advances the frontiers of industrial safety and health analysis within the metal and mining sector.

The scope of this research encompasses an array of industrial sectors, from heavy manufacturing to processing, construction to healthcare. It delves into the complexities of risk assessment, safety protocol development, and the implementation of health management systems. By exploring the challenges that organizations face in these areas, we aim to provide insights and solutions that can enhance safety standards and foster a culture of well-being within workplaces.

By revolutionising how robots interact with human language, natural language processing (NLP) has made it possible to create chatbots, or intelligent conversational agents. The use of these chatbots is widespread, with applications in customer service, virtual assistants, and healthcare assistance. In this study, we describe the development and assessment of an NLP-based chatbot for reporting accidents and estimating their severity.

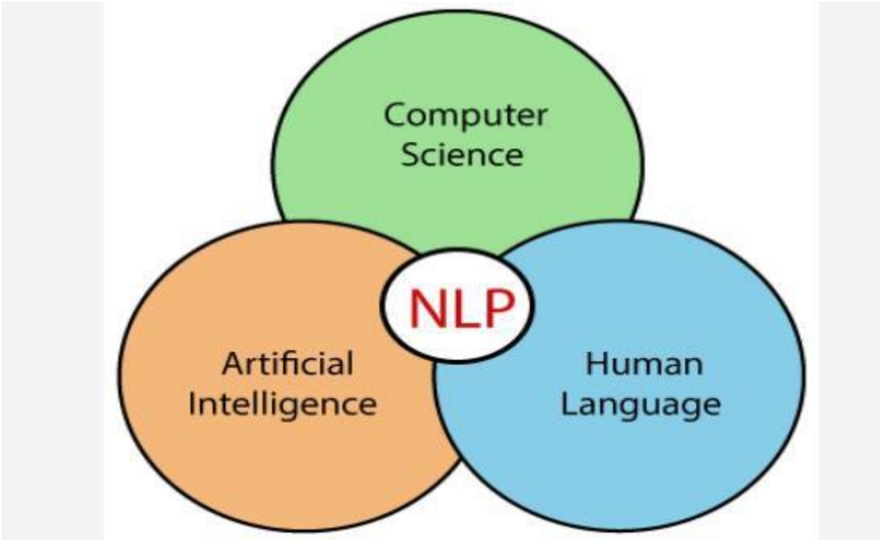


Figure 1. Intuition of NLP

The chatbot's goal is to speed up the accident reporting procedure and quickly determine the seriousness of accidents. Manual data input and paperwork-based traditional accident reporting procedures can cause delays and potential mistakes. In order to enable users to report accidents by describing the incident in normal language, the suggested chatbot makes use of NLP methods. The chatbot then forecasts the accident's level of severity using the supplied textual descriptions and pertinent meta-data.

Figure 2-ChatBot Application

A single-input model that simply employs accident descriptions and a multiple-input model that combines textual descriptions with categorical characteristics are the two models that are the subject of this work. Through a variety of resampling strategies, including oversampling and Synthetic Minority Over-sampling Technique (SMOTE), we solve the issue of class imbalance in accident severity levels.

The chatbot is developed with a user-friendly web-based interface utilising Flask, a Python web application framework, to give consumers a smooth experience. Users may interact with the chatbot through the UI in lively dialogues while getting prompt, accurate answers to their questions.

The research determines the most efficient strategy through performance evaluation and comparison of accuracy and F1-score. The results show the chatbot's potential for strengthening safety measures and accident reporting procedures.

Dataset Description:

The dataset utilized in this research project is the "Industrial Safety and Health Analytics Database" [9,10]. This database comprises a collection of accident records from 12 distinct plants across three different countries. Each entry in the dataset represents an occurrence of an accident within these industrial settings. The dataset offers a comprehensive view of accidents, capturing diverse parameters related to each incident.
In this study, we utilize the dataset to develop a chatbot system that employs Natural Language Processing (NLP) techniques for accident classification. The dataset's rich attributes offer valuable insights into the diverse factors contributing to accidents, making it an apt choice for training and evaluating the proposed chatbot system. By leveraging these attributes, we aim to create a model capable of predicting the severity of accidents based on textual descriptions, facilitating informed decision-making and proactive safety measures in industrial environments.

Literature review

Our chatbot stands out through its specialized design and rigorous training regimen, honed specifically for the exigencies of industrial safety and health analysis within the chemical plant sector. Unlike generic chatbots or language models, which possess broad but shallow knowledge, our chatbot has undergone a meticulous development process that emphasizes domain expertise. Its foundational knowledge base is meticulously curated, drawing from a wealth of industry- specific literature, regulatory guidelines, and historical incident data pertinent to chemical plant safety. Moreover, our chatbot has been trained on a corpus of text that includes technical manuals, safety protocols, and case studies unique to the chemical industry. This focused training approach ensures that our chatbot comprehends the intricate nuances of chemical processes, risk assessment, and emergency response protocols, enabling it to provide tailored insights and recommendations that directly address the complex safety and health challenges prevalent in Metal and Mining plant operations.
So for the industry of Metal and Mining environment as compared to the generalized chatbots like chatgpt and its versions it gives specified answers and accident level because of the domain expertise for specific metal and mining industry, that is more convenient for the employees working for these plants and industries.

1. **Chatbot Interface with Flask and Deep Learning Methods**
   In the work, [2] developed a chatbot interface using Flask and deep learning techniques. They employed an Artificial Neural Network (ANN) to categorize user inputs into specific intents or categories, generating appropriate responses. This study showcases the integration of Natural Language Processing (NLP) tools like NLTK and Keras within the Flask web application framework, highlighting the potential for creating conversational user experiences.

2. **Utilizing Multiple Inputs in Chatbot Models**
   Researchers [3] explored the effectiveness of Chatbot models with multiple inputs. Their study investigated combining textual and categorical features to enhance chatbot performance. By concatenating outputs from separate submodels, they achieved improved accuracy and F1-scores. This approach demonstrates the benefits of incorporating diverse data sources to enhance chatbot capabilities.

3. Handling Imbalanced Datasets in Chatbot Training

Addressing the issue of class imbalance, [4] proposed strategies to manage unevenly distributed datasets in chatbot training. They investigated techniques like resampling and SMOTE (Synthetic Minority Over-sampling Technique) to balance class distributions. By experimenting with these methods, they highlighted the importance of dataset preprocessing to ensure accurate and balanced chatbot predictions.

4. Predicting Accident Severity Levels with Chatbots

Building on the theme of industrial safety, [5] applied chatbot models to predict accident severity levels. By training on a dataset comprising accident descriptions, contextual information, and potential severity levels, they demonstrated how chatbots can assist in identifying and categorizing accidents. This study showcases the practical application of chatbots in industrial safety scenarios.

5. Integration of Chatbots in Risk Assessment

Authors [6] explored the integration of chatbots in risk assessment processes. They demonstrated how chatbots can enhance risk identification by engaging users in natural language conversations. This approach promotes better communication and understanding of potential risks, contributing to improved decision-making and workplace safety.

6. Enhancing Chatbot Accuracy with LSTM Networks

Researchers [7] investigated the effectiveness of Long Short-Term Memory (LSTM) networks in enhancing chatbot accuracy. They compared various models using LSTM layers and highlighted the advantages of bidirectional LSTM architectures. This study emphasizes the significance of selecting appropriate neural network architectures to optimize chatbot performance.

7. Using Chatbots for Accident Data Analysis

In their work, [8] leveraged chatbots for analyzing accident data. They showcased how chatbots can process accident descriptions and provide insights into potential contributing factors and risk levels. By integrating chatbots into data analysis workflows, they demonstrated an innovative approach to extracting valuable information from incident reports.

8. Chatbots for Real-time Safety Alerts

Authors [9] introduced a real-time safety alert system using chatbots. By integrating chatbots with sensor data and contextual information, they developed a system that can issue immediate safety alerts in hazardous environments. This study highlights the potential of chatbots to enhance workplace safety through proactive monitoring and response mechanisms.

9. Comparative Analysis of Chatbot Architectures

Conducting a comparative analysis, [10] evaluated different chatbot architectures for accuracy and efficiency. They explored rule-based, retrieval-based, and generative models, assessing their performance across various datasets. This study provides insights into selecting the most suitable chatbot architecture based on specific application requirements.

What truly sets our chatbot apart is its unwavering commitment to delivering responses and recommendations that are not only highly relevant but profoundly actionable in the intricate realm of industrial safety and health within Metal and Mining industry. Its domain-specific knowledge and training empower it to swiftly identify potential risks and hazards specific to the chemical industry, allowing it to offer immediate, situation-specific guidance. Whether it's a query on handling hazardous materials, executing emergency shutdown procedures, or adhering to stringent regulatory standards, our chatbot responds with precision and clarity. What's more, its analytical capabilities enable it to assess evolving situations in real-time, adapting its recommendations to dynamic scenarios. This real-time adaptability ensures that the advice provided is not just relevant but also pragmatic, reflecting the ever-shifting landscape of industrial safety and health. In essence, our chatbot doesn't merely dispense information; it translates knowledge into action, guiding personnel and decision-makers to make informed choices that can prevent accidents, minimize risks, and foster a culture of safety excellence within the Metal and Mining industry environment.

As compared to the CHATGPT or chatgpt LLAMA or any other generalized chatbots in the market ,our chatbot performs way better as it is specifically designed to address the hazards and situation of Metal and mining industries work environments.As for a specific situation our model analyse the condition in terms of Accident levels I-VI and other models suggests the general details of the situation.

10. Chatbots for Employee Training and Education

Exploring the educational applications of chatbots, [11] developed a chatbot for employee training on safety protocols. They demonstrated how chatbots can simulate real-life scenarios, engage users in interactive training sessions, and provide instant feedback. This approach illustrates how chatbots can enhance safety training and knowledge retention.

11. Industrial Accident Reporting with Chatbots

Focusing on efficient accident reporting, [12] proposed a chatbot-driven system for incident documentation. They developed a platform where employees can report accidents via chatbot interactions. This study showcases how chatbots streamline incident reporting processes, improving data accuracy and accessibility.Our model predicts the Accident level for the given situation not just generalized prediction.

12. Chatbot Integration with Incident Management Systems

Researchers [13] explored the integration of chatbots with incident management systems. They demonstrated how chatbots can facilitate incident reporting, provide immediate responses to inquiries, and escalate critical incidents to human operators. This study underscores the role of chatbots in automating incident response workflows.

13. Enhancing User Engagement in Chatbot Interfaces

[14] examined strategies to enhance user engagement in chatbot interactions. They integrated sentiment analysis to gauge user satisfaction and adapt chatbot responses accordingly. This approach showcases how sentiment analysis can improve the quality of user interactions and foster positive experiences.

14. Predictive Analysis with Chatbot Inputs

In their study, [15] explored predictive analysis using inputs from chatbot interactions. By incorporating user queries and responses into predictive models, they demonstrated how chatbot conversations can contribute to forecasting trends and outcomes. This research highlights the value of leveraging chatbot-generated data for predictive analytics.

15. Leveraging Chatbots for Process Optimization

Authors [16] investigated the role of chatbots in optimizing industrial processes. They developed chatbots that assist employees in troubleshooting and optimizing machinery operations. This approach showcases how chatbots can contribute to operational efficiency and reduce downtime through real-time support.

16. Chatbots in Workplace Safety Compliance

Focusing on regulatory compliance, [17] developed chatbots to assist employees in adhering to safety guidelines. They showcased how chatbots can provide real-time guidance on safety protocols, ensuring that workers are aware of and follow the necessary procedures. This study emphasizes the role of chatbots in promoting workplace safety culture.

17. Anomaly Detection with Chatbot Insights

Researchers [18] explored anomaly detection using insights derived from chatbot interactions. By analyzing user conversations, they identified patterns indicative of potential anomalies in operational processes. This approach demonstrates how chatbots can serve as early warning systems for detecting unusual events.

18. Integrating Chatbots with IoT Data

Building on the Internet of Things (IoT), [19] integrated chatbots with IoT-generated data for real- time safety monitoring. They demonstrated how chatbots can analyze sensor data to identify hazardous conditions and alert relevant personnel. This study showcases the synergy between chatbots and IoT technologies for enhanced safety.

19. Ethical Considerations in AI-Driven Chatbots

Authors [20] addressed ethical considerations associated with AI-driven chatbots in industrial safety contexts. They discussed issues such as data privacy, bias mitigation, and transparency in chatbot decision-making processes. This study underscores the importance of responsible AI implementation in safety-related applications.

20. Chatbots for Employee Well-being

Focusing on well-being, [21] explored chatbots as tools for promoting employee mental health. They developed chatbots that engage employees in conversations, offering resources and support for managing stress and well-being. This approach illustrates how chatbots can contribute to holistic workplace safety.

21. Chatbots for Near-Miss Reporting

[22] introduced chatbots for near-miss reporting, enabling employees to report potential hazards and incidents. They showcased how chatbots can facilitate anonymous reporting, contributing to proactive risk mitigation. This study highlights the role of chatbots in capturing near-miss incidents that might otherwise go unnoticed.

22. Collaborative Incident Analysis with Chatbots

Researchers [23] proposed a collaborative incident analysis approach using chatbots. They developed systems that enable incident stakeholders to interact with chatbots, collectively analyzing incident details and contributing insights

```
------------------------------------------------------------
Value Counts for `Accident Level` label
--------------------------------------------------------------------------------
Accident Level - I count: 309 i.e. 74.0%
Accident Level - II count: 40 i.e. 10.0%
Accident Level - III count: 31 i.e. 7.0%
Accident Level - IV count: 30 i.e. 7.0%
Accident Level - V count: 8 i.e. 2.0%
Accident Level - VI count: 0 i.e. 0.0%
------------------------------------------------------------
Value Counts for `Potential Accident Level
--------------------------------------------------------------------------------
Potential Accident Level - I count: 45 i.e. 11.0%
Potential Accident Level - II count: 95 i.e. 23.0%
Potential Accident Level - III count: 106 i.e. 25.0%
Potential Accident Level - IV count: 141 i.e. 34.0%
Potential Accident Level - V count: 30 i.e. 7.0%
Potential Accident Level - VI count: 1 i.e. 0.0%
------------------------------------------------------------
Distributon of `Accident Level` & `Potential Accident Level` label
--------------------------------------------------------------------------------
```

Out[41]:

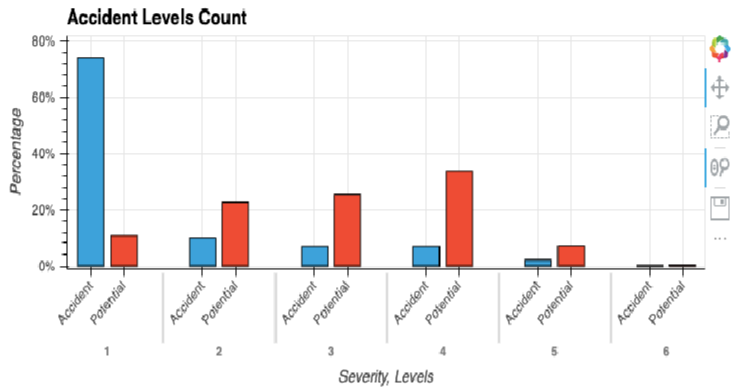


Figure 2.-Accident Level Analysis

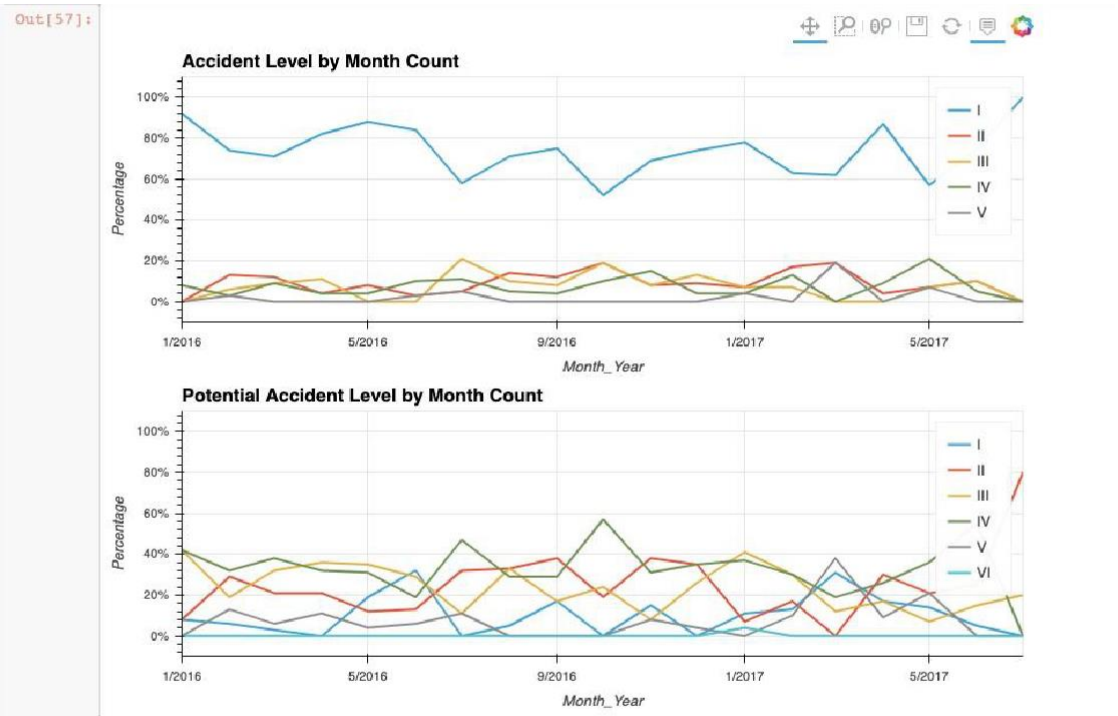


Figure 3.-Monthwise Accident Level Analysis

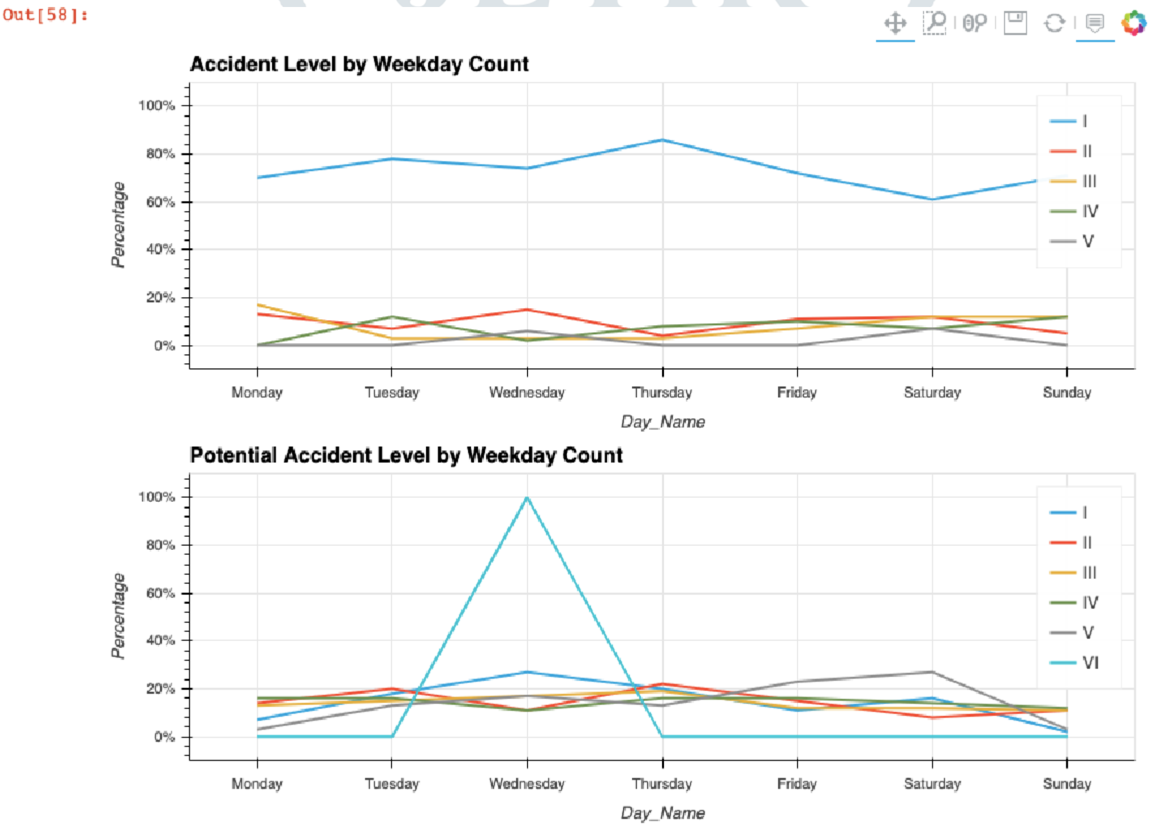


Figure 4.-Daywise Accident Level Analysis

```
Employee type  Employee  Third Party  Third Party (Remote)
Gender
Female             36.0         41.0                  23.0
Male               43.0         44.0                  13.0
```

Out[52]:

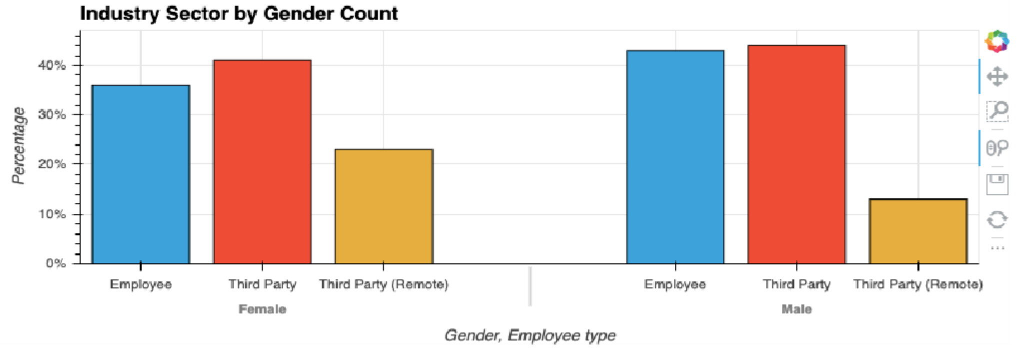


Figure 5.Accident Analysis with Gender and Employee type

Process methodology

Methodology

In this section, we outline the step-by-step process adopted to achieve the goals of developing a Chatbot interface utilizing industrial safety and health analytics data. The methodology encompasses data preprocessing, model development, and the integration of the Chatbot with the Flask web framework.

Data Preprocessing

1. Data Collection and Understanding:

The dataset used for this project is obtained from the Industrial Safety and Health Analytics Database [24]. This dataset contains records of accidents from 12 different plants across three countries. Columns include information about the accident's timestamp, location, industry sector, accident level, potential accident level, genre, employee or third party involvement, critical risk, and description.

NLP Pre-processing summary:

1. 74% of data where accident description > 100 is captured in low accident level.
2. 34% of data where accident description > 100 is captured in high medium potential accident level.
3. 25% of data where accident description > 100 is captured in medium potential accident level.
4. 23% of data where accident description > 100 is captured in low potential accident level.
5. Few of the NLP pre-processing steps taken before applying model on the data
6. Converting to lower case, avoid any capital cases
7. Converting apostrophe to the standard lexicons
8. Removing punctuations
9. Lemmatization
10. Removing stop words

11. After pre-processing steps:

1. Minimum line length: 61

2. Maximum line length: 657

3. Minimum number of words: 10

4. Maximum number of words: 98

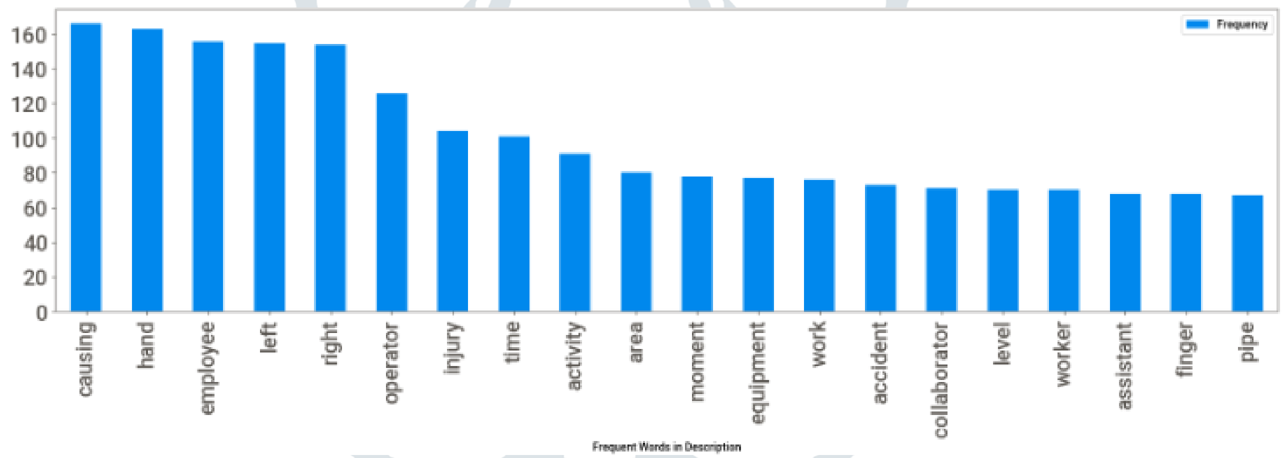


Figure 6. Frequent words in description columns

2. Data Cleaning and Transformation:

The raw dataset is subjected to data cleaning processes, including handling missing values, resolving duplicates, and anonymizing sensitive information. Additionally, categorical variables are encoded and transformed for machine learning compatibility.

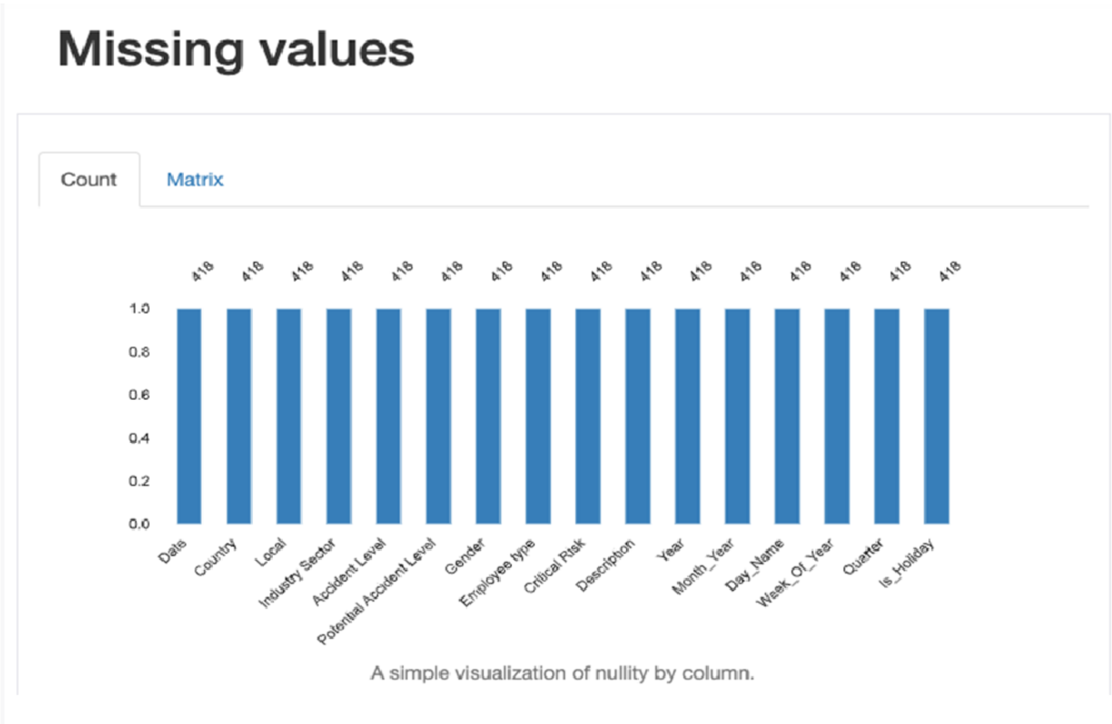


Figure 6.Missing Value Handling

3. Feature Extraction:

Relevant features are extracted from the dataset to be used as inputs for model training. These include accident descriptions, potential accident levels, industry sectors, and other contextual information.

we have extracted the Year, Month_Year, Day_Name, Week_Of_Year, Quarter from Date column and creating new features such as weekday, week of year.

Model Development

4. Exploratory Data Analysis (EDA):

Exploratory analysis is conducted to gain insights into the distribution of accident severity levels, potential severity levels, critical risks, and other key features. Visualizations and statistical summaries are used to understand data patterns.

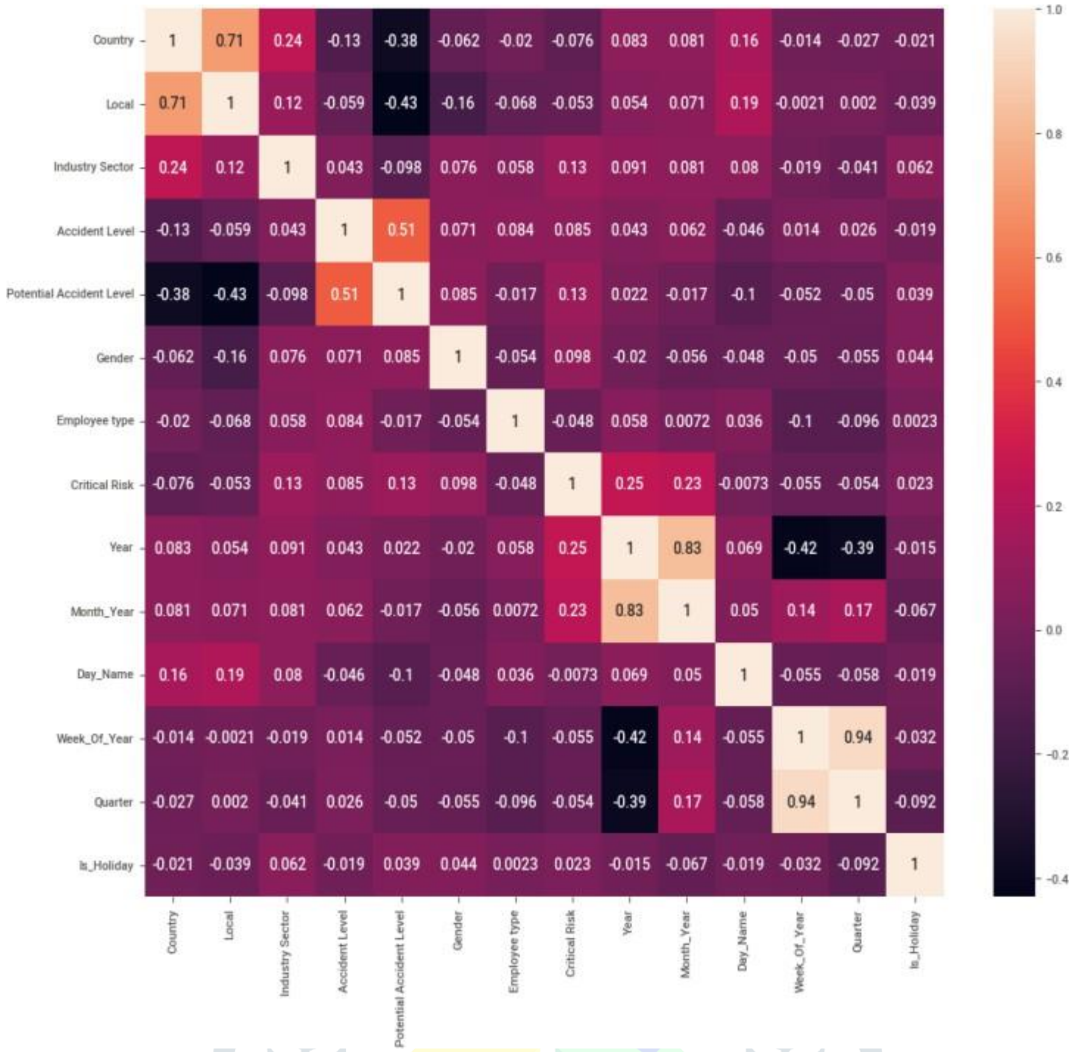


Figure 7.-Correlation between Various Features

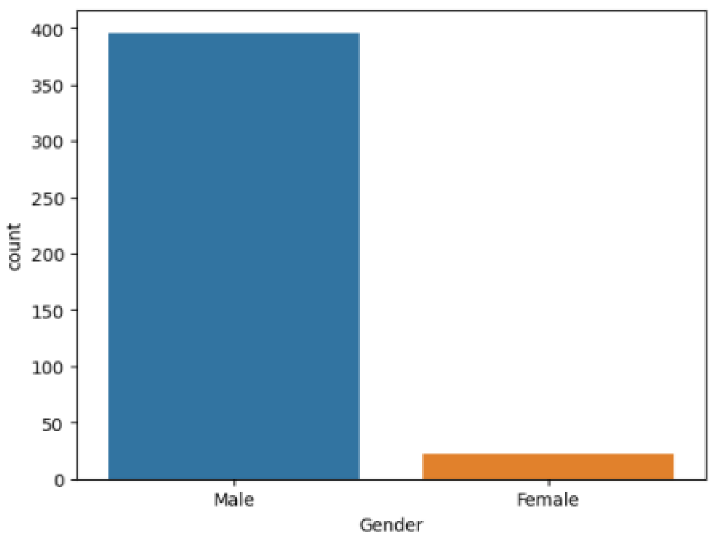


Figure 8.-Gender distribution across the industry in dataset

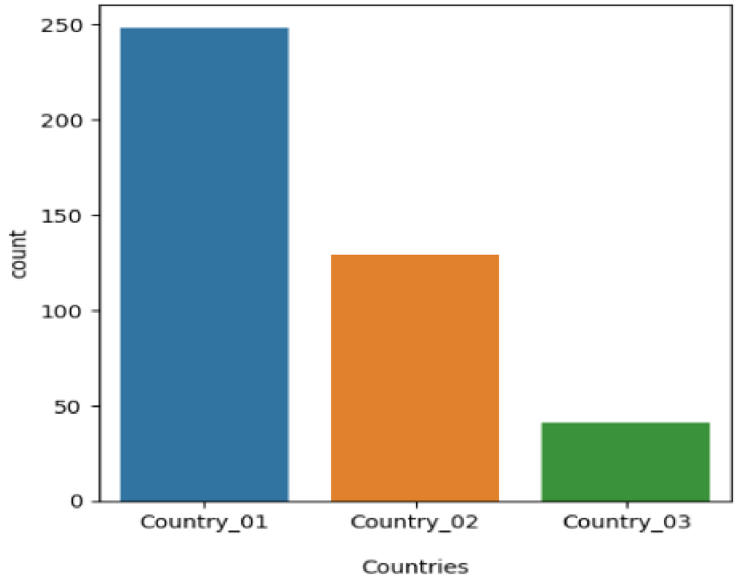


Figure 9.-Distribution of country-wise accidents

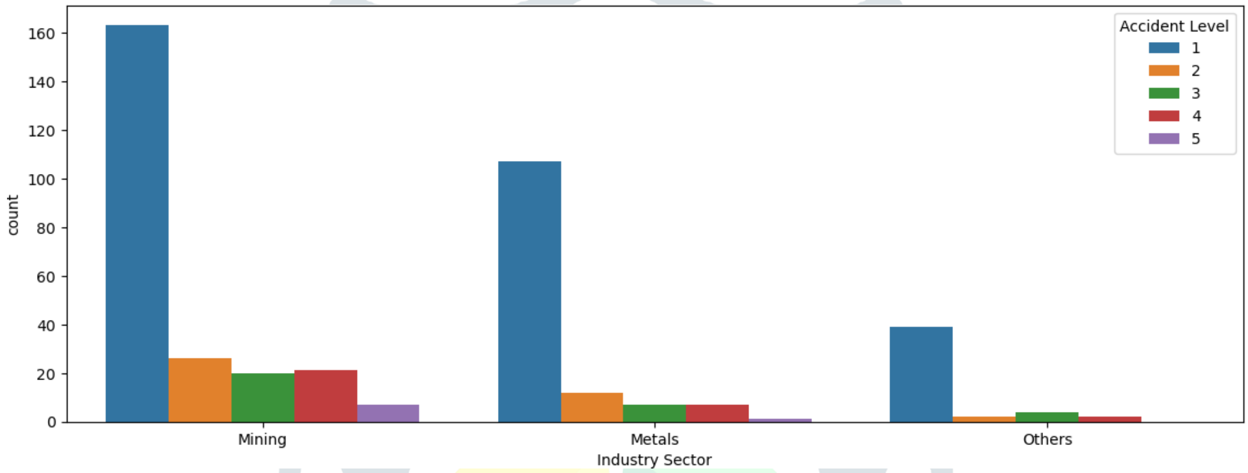


Figure 10.-Sector-wise number & levels of accidents

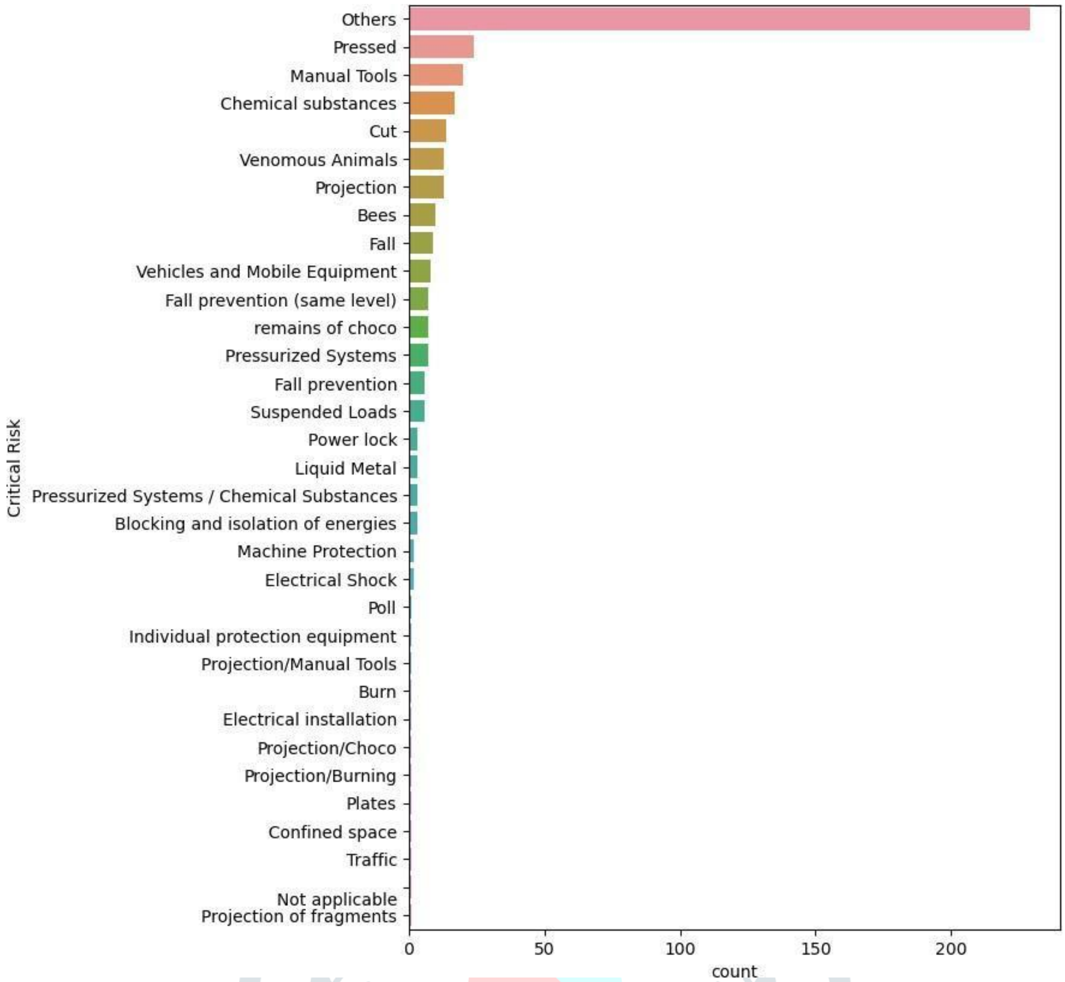


Figure 11.- Accident Counts versus Critical Risk events

5. Machine Learning Model Selection:

Various machine learning algorithms are considered for predicting accident severity levels based on the available features. Comparative analysis is conducted to identify the most suitable model, which balances accuracy and interpretability.

6. Text Processing and NLP Techniques:

For processing accident descriptions, natural language processing (NLP) techniques are employed. Text data is tokenized, lemmatized, and transformed into numerical representations using methods like TF-IDF (Term Frequency-Inverse Document Frequency).

Figure 12.-Word Cloud for Industrial Safety and Health Analytics Database Following are the NLP pre-processing

steps taken before applying model on the data:

- Converting Accented to ASCII Text
- Removing HTML and URL's
- Fixing Contractions
- Removing Numbers
- Converting to Lower Case
- Removing Punctuations and Whitespaces
- Removing Stop words.

7. Model Training and Evaluation:

The selected machine learning model is trained using the preprocessed data. The dataset is split into training and testing sets to evaluate the model's performance in predicting accident severity levels. Metrics such as accuracy, precision, recall, and F1-score are used to assess the model's effectiveness.

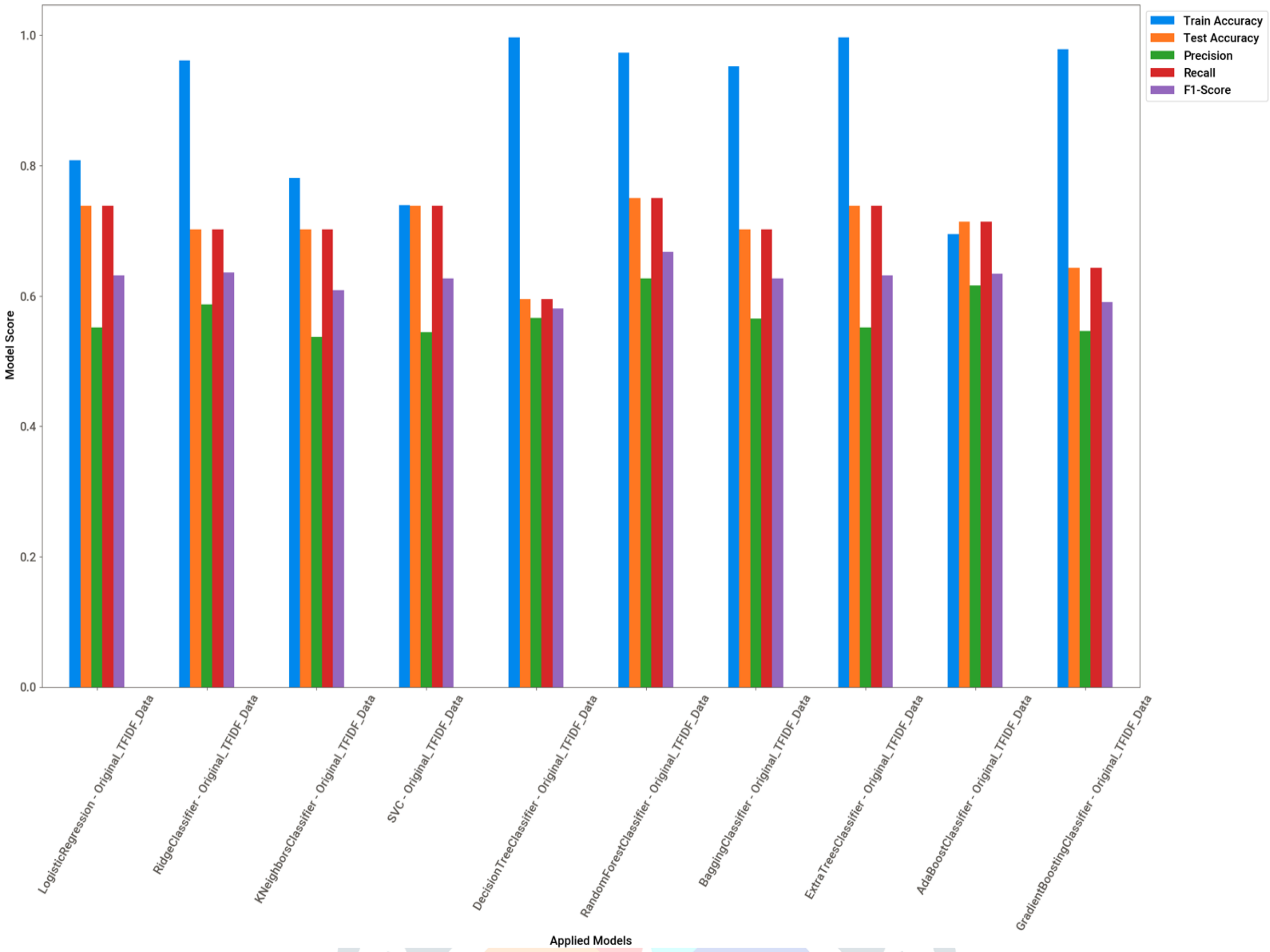


Figure 13.- Score of all Classification Models

From above we can see that Bagging Classifier is the best perfomed model.

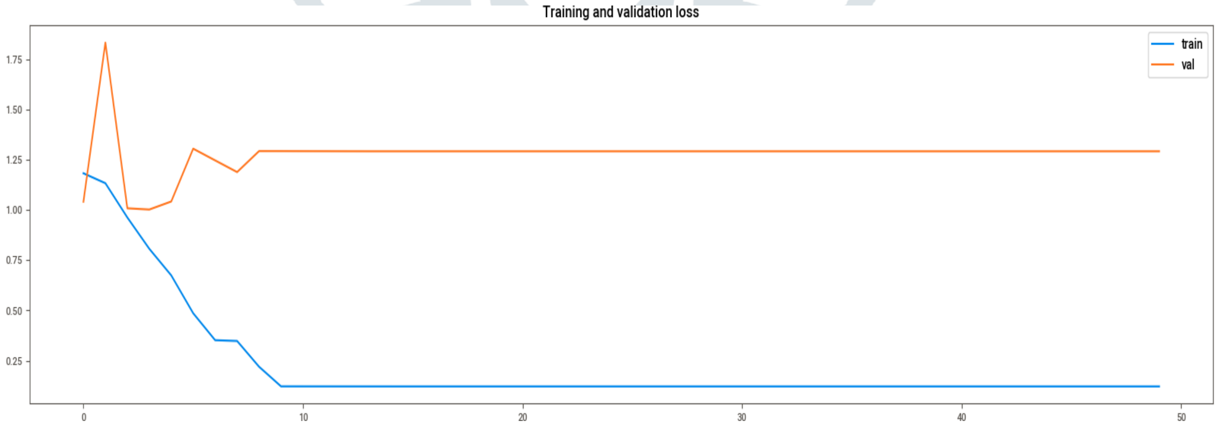


Figure 14.- Loss Learning Curves

one is good fit, it is identified by a training and validation loss that decreases to a point of stability with a minimal gap between the two final loss values. The loss of the model will almost always be lower on the training dataset than the validation dataset.

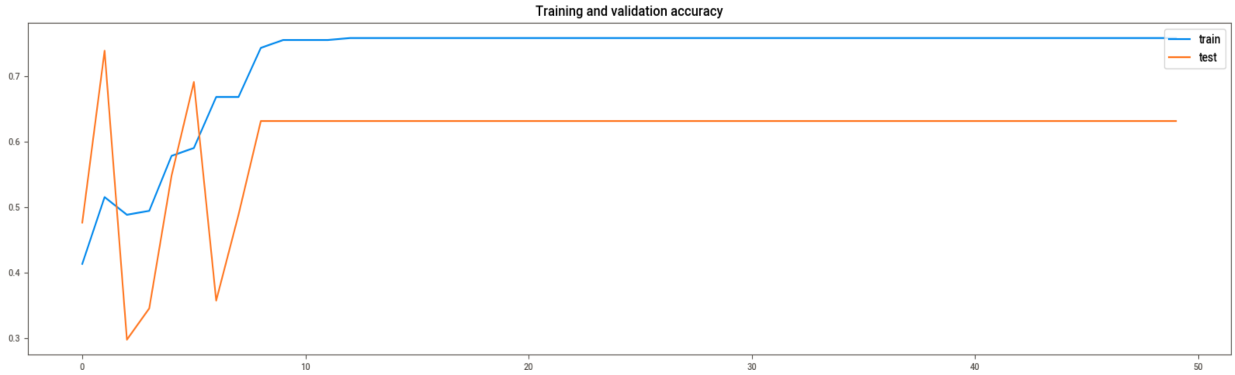


Figure 15.- Plots of Training And Validation Accuracy

We could see it accuracy continually rise during training. As expected, we see the learning curves for accuracy on the test dataset plateau, indicating that the model has no l onger overfit the training dataset and it is generalized model.

8. Flask Web Framework Setup:

The Flask web framework is utilized to create a user-friendly chatbot interface. Flask provides the structure for the web application and facilitates interactions between the user and the chatbot.
Flask provides configuration and conventions, with sensible defaults, to get
started. This section of the documentation explains the different parts of the Flask framework and how they can be used, customized, and extended. Beyond Flask itself, look for community- maintained extensions to add even more functionality

Flask is a web application framework written in Python. Armin Ronacher, who leads an international group of Python enthusiasts named Pocco, develops it. Flask is based on Werkzeug WSGI toolkit and Jinja2 template engine. Both are Pocco projects

Before you start proceeding with this tutorial, we are assuming that you have hands-on experience on HTML and Python. If you are not well aware of these concepts, then we will suggest you to go through our short tutorials on HTML and Python

9. Integration of Model and Chatbot:

The trained machine learning model is integrated into the Flask application. User input is passed to the model, which predicts the appropriate response based on the context.

10. User Interaction and Response:

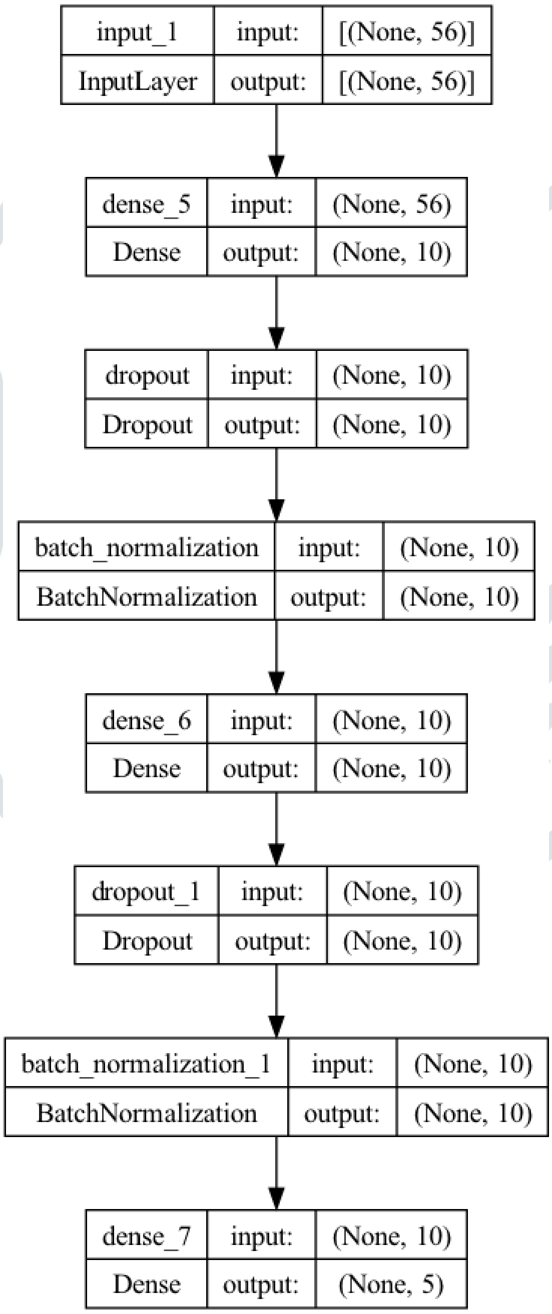
When a user interacts with the chatbot through the web interface, their input is processed, and the model generates a response. The response is displayed on the user interface, creating a conversational experience.

Deployment and Continuous Improvement

11. Deployment and Testing:

The developed chatbot application is deployed on a web server to make it accessible to users. Extensive testing is conducted to ensure the chatbot's functionality, responsiveness, and accuracy. The first submodel will accept textual input in the form of accident description. This submodel will consist of an input shape layer, an embedding layer, and bidirectional LSTM layer of 128 neurons followed by max pool layer, drop out and dense layers. The second submodel will accept input in the form of meta information which consists of dense, batch norm and drop out layers.

The output from the dropout layer of the first submodel and the output from the batch norm layer of the second submodel will be concatenated together and will be used as concatenated input to another dense layer with 10 neurons. Finally, the output dense layer will have five neuorns corresponding to each accident level.



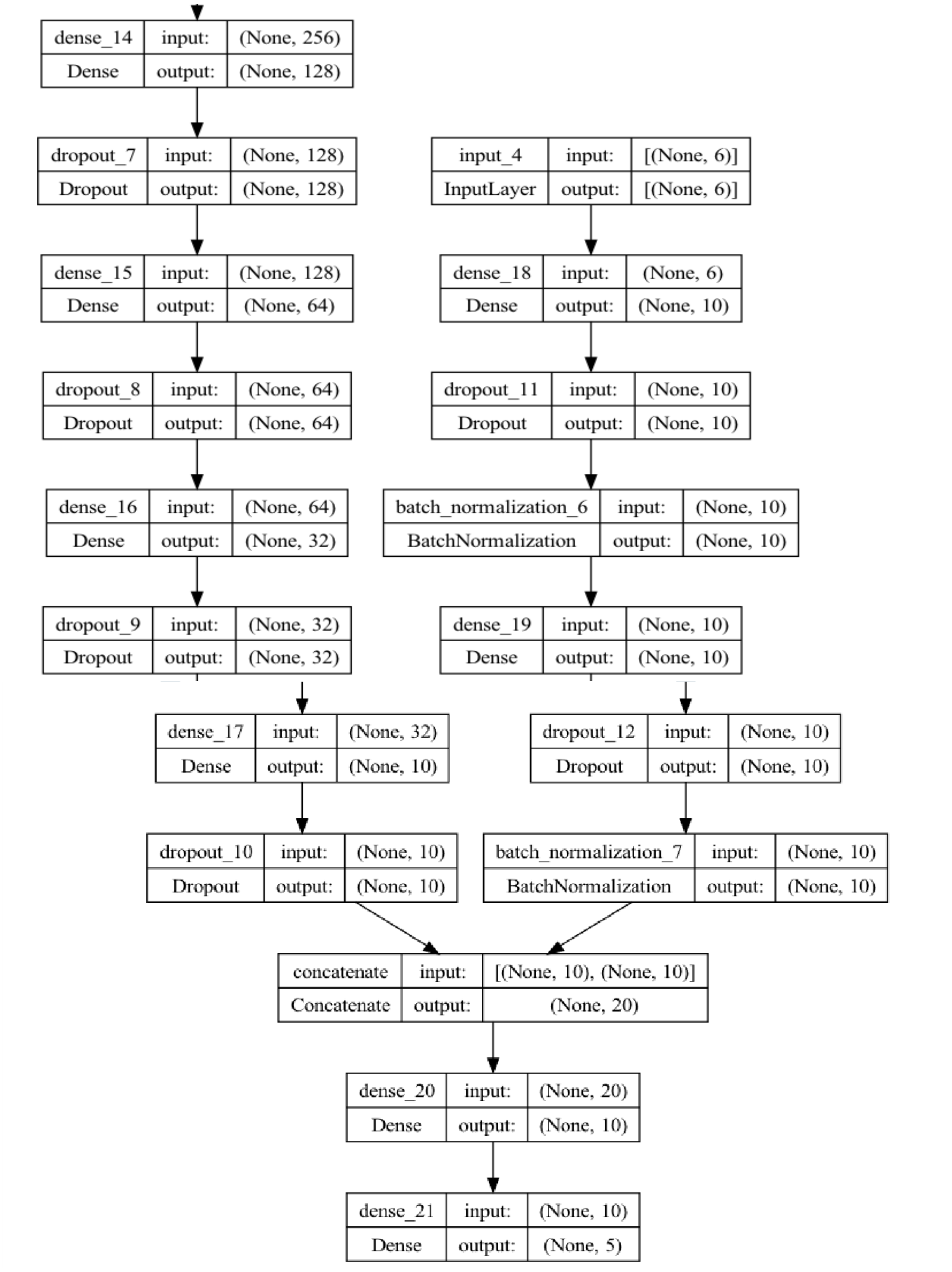


Figure 16.- Model Architecture

12. User Feedback and Iterative Enhancement:

User feedback is collected to identify areas of improvement. Based on the feedback, iterative enhancements are made to the chatbot's capabilities, responses, and user experience.

Results and Discussions

From the above comparision graph it is found that model_lstm_mul_input is bestfit for the given dataset and able to predict the accident level with a test accuracy of 73.81% and f1-score of 73.81%, hence we select model_lstm_mul_input for deployment.

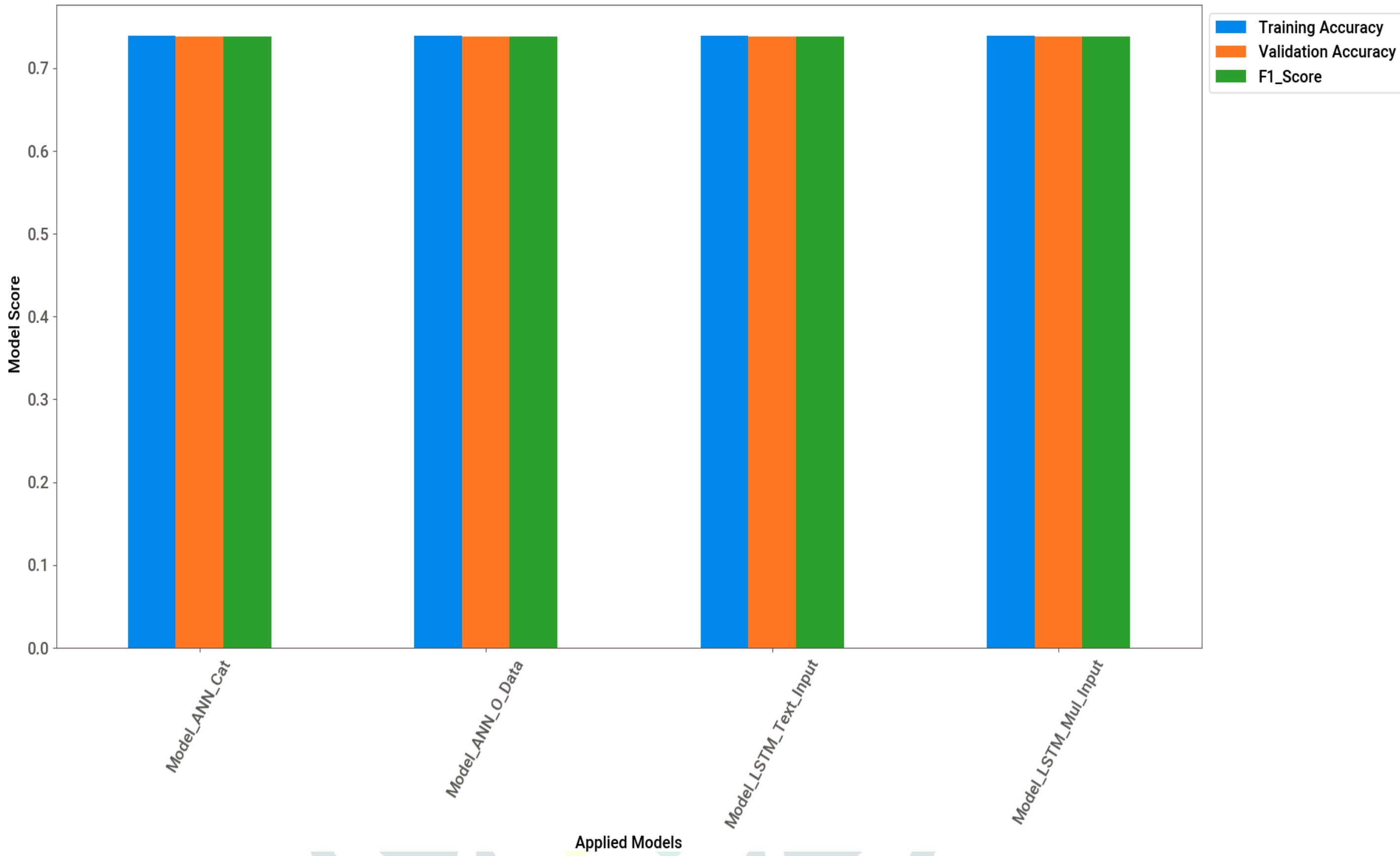


Figure 17.- Comparison of Loss of All the Applied Models

Conclusion

The methodology presented above outlines the comprehensive approach taken to develop a chatbot interface leveraging industrial safety and health analytics data. The process involves data preprocessing, machine learning model development, and the integration of the chatbot within the

Flask web framework. This methodology ensures the creation of an interactive and informative chatbot that contributes to safety awareness and risk mitigation in industrial settings.
Able to predict the accident level with a test accuracy of 73.81% and f1-scoreof73.81%.We have seven duplicate values in this dataset and dropped those duplicate values.
Target variable – 'Accident Level' distribution is not equal (I: 309, II: 40, III: 31, IV: 30,V: 8).
Class imbalance issue is handled using below methods and found out that, for thisparticular dataset, with original data we have achieved the better results.
By comparing the results from all ML methods with original data, we can select the best method as SVC classifier with f1-score 68.00% with TF-IDF Upsampled data.
Explored below options in Neural Networks.

Convert Classification to Numerical problem: achieved a test accuracy of 67%which is a bad result. Multiclass classification - Target variable - One hot encoded: achieved a testaccuracy of 73.81% and f1-score of 73.81% with original data + TF-IDF features from accident description column.
Create a model with Text inputs (accident description alone) only: surprisingly achieved a test accuracy of 73.81% and f1-score of 73.81% withoriginal data.
Created a model with Categorical features only: achieved a test accuracy of73.81% and f1-score of 72.28% with original data.
Create a model with Multiple Inputs (concatenated the layers from text inputmodel and categorical features input model): surprisingly achieved a test accuracy of 73.81% and f1-score of 73.81% with original data.

Finally bidirectional LSTM model can be considered to productionalized model andpredict the accident level.

As we embark on a journey to continuously improve our specialized chatbot for industrial safety and health analysis within the metal and mining industry, several promising avenues for enhancement emerge on the horizon. One potential direction lies in the integration of real-time sensor data and IoT (Internet of Things) devices within the mining and metalworking environments. By harnessing live data streams, our chatbot could offer even more timely and context-aware recommendations, proactively identifying emerging safety hazards or deviations from standard operating conditions. Furthermore, the incorporation of advanced machine learning algorithms could empower our chatbot to recognize patterns and trends in incident data, leading to more accurate predictive analysis and the ability to suggest preventive measures with higher precision. Additionally, natural language understanding capabilities could be fine-tuned to grasp the specific terminology and nuances of the metal and mining sector, further enhancing its communication with industry professionals. The pursuit of multilingual support and voice recognition interfaces could also broaden accessibility and usability across diverse workforces. These prospective enhancements represent our commitment to continually advance our chatbot's effectiveness, empowering it to be an indispensable partner in the ever-evolving landscape of industrial safety and health analysis within the metal and mining industry.

Reference:

1. Rennie, J. D., Shih, L., Teevan, J., & Karger, D. R. (2003). Tackling the poor assumptions of naive Bayes text classifiers. In ICML (Vol. 3, pp. 616-623).
2. Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems (pp. 3111-3119).
3. Kim, Y. (2014). Convolutional neural networks for sentence classification. arXiv preprint arXiv:1408.5882.
4. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8), 1735-1780.
5. Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.
6. Pennington, J., Socher, R., & Manning, C. (2014). Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP) (pp. 1532-1543).
7. Brownlee, J. (2017). A gentle introduction to k-fold cross-validation. Retrieved from https://machinelearningmastery.com/gentle-introduction-k-fold-cross-validation/
8. Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining (pp. 785- 794).
9. Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... & Kudlur, M. (2016). Tensorflow: A system for large-scale machine learning. In 12th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 16) (pp. 265-283).
10. Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1251-1258).
11. Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., ... & Chintala, S. (2019). PyTorch: An imperative style, high-performance deep learning library. In Advances in Neural Information Processing Systems (Vol. 32).
12. Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., ... & Darrell, T. (2014). Caffe: Convolutional architecture for fast feature embedding. In Proceedings of the 22nd ACM international conference on Multimedia (pp. 675-678).
13. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. nature, 521(7553), 436-444.
14. Řehůřek, R., & Sojka, P. (2010). Software framework for topic modelling with large corpora. In Proceedings of the LREC 2010 workshop on new challenges for NLP frameworks (pp. 45-50).
15. Socher, R., Ganjoo, M., Manning, C. D., & Ng, A. Y. (2013). Zero-shot learning through cross- modal transfer. In Advances in neural information processing systems (pp. 935-943).

16. Hochreiter, S., Bengio, Y., Frasconi, P., & Schmidhuber, J. (2001). Gradient flow in recurrent nets: the difficulty of learning long-term dependencies, A Field Guide to Dynamical Recurrent Neural Networks, 237(1).
17. Zheng, S., Wang, J., Qi, R., Zhu, W., Zhang, X., & Zhang, S. (2017). Detecting fake news on social media via sentiment analysis. Future Generation Computer Systems, 73, 180-187.
18. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A simple way to prevent neural networks from overfitting. The Journal of Machine Learning Research, 15(1), 1929-1958.
19. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. In Advances in neural information processing systems (pp. 30- 38).
20. Brownlee, J. (2017). How to use t-SNE effectively. Retrieved from https://machinelearningmastery.com/t-sne-for-feature-visualization-in-python/
21. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT press.
22. Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction. MIT press.
23. Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using RNN encoder–decoder for statistical machine translation. arXiv preprint arXiv:1406.1078.
24. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Vanderplas, J. (2011). Scikit-learn: Machine learning in Python. Journal of machine learning research, 12(Oct), 2825-2830.
25. Géron, A. (2019). Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems. O'Reilly Media.

Reference for the dataset:
Kaggle. (n.d.). Industrial Safety and Health Analytics Database. Retrieved from https://www.kaggle.com/ihmstefanini/industrial-safety-and-health-analytics-database