

**National College of Ireland**  
**Project Submission Sheet**

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### Deep Learning-Based Prediction of Lithium Battery Fire Risk Using Real-World Incident Data

Your Name/Student Number	Course	Date
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# Deep Learning-Based Prediction of Lithium Battery Fire Risk Using Real-World Incident Data

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**Abstract:** The use of lithium-ion batteries has increased due to its high energy density; long life cycle, and has higher performance compared to traditional batteries, making them the reason to adopt widely in electrical vehicles and portables devices [1]. As we can see, there are advantages of using lithium batteries but there are also disadvantages of using which are related to safety concerns particularly related to the overcharging of batteries, physical damage or the manufacturing defects. This paper proposes a deep learning-based predictive model to classify and assess fire risk which is based on the real incident form the London fire brigade [2]. For this study we have applied CRISP-DM methodology by encoding categorical features from the historical incident that occurs and trained artificial neural network. The trained model achieved a accuracy of 84.76%, with strong F1-scores demonstrating the potential of deep learning which could enhance the safety monitoring and fire risk prediction in EV related environments.

**Keywords—** Lithium-ion batteries, Electric vehicles (EVs), Incident classification, Deep learning.

## INTRODUCTION

Lithium-ion batteries have become the primary energy source for electric vehicles (EVs) and portable electronic devices due to their high energy density, long life cycle, and fast charging capabilities [3]. These qualities make them cornerstone of technology in the growing electric mobility and energy storage sectors. However, their growing usage, serious fire and safety concerns have emerged particularly speaking for overcharging, mechanical stress, thermal exposure and sometimes poor built quality [4].

Recent studies show that failure like electrolyte leakage, separator breakdown, electrode material degradation and internal short circuits sometimes results in critical thermal runaway events [5]. These failures can cause excessive heat, pressure or impact during operations or charging cycles. Once the thermal runaway begins it becomes self-sustaining

leading to rapid temperature rise, releases flammable gases and violent fire or explosion scenarios [6].

The experiment was conducted lighting the fire to lithium-ion battery packs which reveal that they emits high pressure jets of flame and toxic gases like hydrogen fluoride (HF) during thermal runaway, making them extinguish more difficult [6]. Furthermore, aging of batteries, improper design of battery management systems and uneven cell charging can accelerate degradation and increase vulnerability of fire [5].

To address these escalating concerns, this study proposes a deep learning- based fire risk prediction model using real-world dataset from London fire brigade [2]. The model is designed to classify whether a reported incident involved lithium-ion batteries or not. For this study we have applied CRISP-DM (Cross-Industry Standard Process for Data Mining) framework, which include data cleaning, encoding of categorical features , model design , training and evaluation.

## RELATED WORKS

Recent advancements in fire risk prediction from battery-powered systems have leveraged various data-driven and machine learning methodologies which we will be discussing. Bisschop et al. [6] conducted a comprehensive study on fire safety risks with is related to lithium-ion batteries on road vehicles, which focused on thermal runaway mechanism, suppression systems, release of toxic gas emissions and standard fire testing methods. Their report presents the real-world fire scenarios and post incident hazards management particularly the dangers of hydrogen fluoride (hf) gas release. Their work strength lies in the regulatory alignment and relevance to automative safety. However, it lacks a data driven modeling approach and focuses only on post failure but our study includes a deep

learning model that proactively classifies lithium battery fire incidents using historical data and CRISP-DM methodology enable early risk identification before failure occurs [6].

The second paper conducted large-scale fire tests on electric vehicles on actual road tunnel environment. The authors focused on comparing heat release rates (HRR), toxic gases, and firefighting strategies between battery powered vehicles and internal combustion engine vehicles. However, a key limitation of this study lacks predictive modeling. The study is pure experiments and does not attempt to forecast fire risk incidents [7]. Additionally, the third paper extended this domain by analyzing combustion risks in enclosed structures such as garage using computational fluid dynamic (CFD) they highlighted the unique challenges of managing EV fires in confined spaces but similarly did not employ data driven technique [8]. Our work adopts a predictive and proactive approach using deep learning. And in our study, we will not only analyze post fire metrics like HRR, but we will be doing by the structured historical data to train our neural network classifier. This will allow us for early identifications of fire risk.

The fourth paper discusses the in dept review of electric vehicle fire hazards which emphasize the significant risk of counterfeit lithium-ion batteries. The paper outlined the thermochemical behavior of genuine vs counterfeit battery packs, highlighting fire initiation mechanism, heat release rates and smoke toxic. A key strength of their study is that they focus on real world safety scenarios especially within urban environment. But considering that they lack predictive modeling and, they have not used AI technique which limits their applicability in automated safety systems. Compared with our study it is proactive risk classification, and we have applied deep learning techniques which will predict the fire before it occurs [9]. The fifth paper discusses the study on risk prevention and recovery strategies for lithium-ion batteries in electric vehicles focusing on hazardous events arising traffic accidents. The paper excels in outlining practical safety protocols, such as isolation zones, battery packs deactivations procedures and fire suppression system designs especially water mist and spray systems. However, the research is purely experimental and descriptive, but it lacks any predictive modeling techniques that could anticipate fire risks before they occur. Our work differs significantly by using deep learning and we will detect the incident before it arises [10].

The sixth conducted a performance-based fire safety of EV cars within car parks which are growing threats posed by lithium batteries. The strength of their paper lies in the detailed CFD based simulations using fire Dynamics Simulator. With this help of analysis, they came with actionable insights for evacuation planning and fire brigade

response. However, the study reactive its focus on fire behavior after ignition rather than predicting it before and where our study exceeds in that [11]. The seventh paper proposed a numerical simulation approach to analyze the fire behavior of lithium-ion batteries in new energy vehicles within tunnel environment. The study used pyroSim and FDS software to simulate the effects of various heat release rate and temperature distribution. The main strength of their paper lies in its comprehensive simulation of real-world tunnel incidents and detailed evaluation of thermal plumes smoke layers and toxic gases dispersion. The study particularly highlights critical risks of CO/CO<sub>2</sub> accumulation and visibility reduction during tunnel fires valuable for emergency response planning. However, the major limitation is the absence of any predictive mechanism. The study does not integrate real world incident datasets. Our work differs by shifting focus from physical simulation to predictive modeling. Instead of simulating tunnel fires we utilize historical incident data [12].

In the eight papers they have mentioned a in depth experiment study on thermal runaway and contamination from electric vehicle lithium-ion batteries in enclosed infrastructure environment. Their study strengthens the multi scenario fire experiments covering infrastructure contamination, water pollution and long-range soot dispersion. Through comprehensive chemical and metallurgical analyses, the author identified significant concentrations of toxic and corrosive residues, including heavy metals that persist post-fire. However, they lack predictive modeling limits its preventive capabilities. The research is purely descriptive and retrospective [13]. The ninth paper provides a review of opportunities and challenges surrounding lithium-ion batteries in electric vehicles. The paper covers critical aspects such as electrode material advancements battery form factors and emerging technologies like solid state batteries and silicon anodes. Their paper strength lies in the board market perspective examining future trends in energy density improvements, thermal management and cost reductions for various vehicle categories. However, the review has notable limitations, it is entirely descriptive and does not implement any computational models. Additionally, they lack empirical experimentation, or simulation limits its applicability for operational deployment [14].

The next paper discusses about fire risks of Ev cars in Australia, they have utilized secondary data and statistical models to forecast EV growth and incidents trends until 2050. Their project get strength from the use of historical fire data and policy documents to project future risks and provide a risk mitigation framework. However, they lack machine learning or AI based modeling where the author relied on Excel based statistical forecasting which may not adapt well

to real time dynamic risk environment. In contrast our work proposes a proactive approach using advanced classifiers [15].

## METHODOLOGY

This study follows the CRISP-DM ( Cross – Industry Standard Process for Data Mining ) methodology, which provides a structured and iterative approach for developing and deploying predictive models. The six phases of CRISP-DM are mapped into our workflow to ensure a systematic application for deep learning.

### 1. Business Understanding

The project aims to predict whether an incident involves a lithium – ion battery fire using structured emergency report data. This will help the fire service and public safety agencies by enabling early detection and prevention of high-risk fire cases in EV.

### 2. Data Understanding

For this project we have used a real - world dataset source from the London Fire Brigade, which contains various attributes such as ignition source, power type , item first ignited, vehicle manufacture and geographical information. The target column labelled whether lithium batteries were involved in the incident. Exploratory data analysis (EDA) was performed to assess feature distributions, missing values and class imbalance.

### 3. Data Preparation

To prepare the data for deep learning.

- Missing Values in categorical columns (e.g. ignition source, power type) were filled with “Unknown”.
- Categorical encoding was applied using Label Encoding to convert text data into numeric format.
- The final dataset included only relevant features and the target binary label.
- Feature scaling was applied using StandardScaler to normalize input values for neural network training.

### 4. Modeling

We developed a feedforward Artificial Neural Network (ANN) using TensorFlow with the following architecture.

#### 1. First Hidden Layer

- It contains 64 neurons.
- Activation function called ReLU (Rectified linear Unit) is applied.
- And we connected directly to the input layer.

#### 2. Dropout Layer (after first hidden layer)

- The drop out rate is 30%
- Randomly deactivates 30 % of neurons during training to prevent overfitting and improving generalization.

#### 3. Second Hidden Layer

- This contains 32 neurons also using ReLU activation.
- This layer captures more abstract interactions between features and add depth to the network .

#### 4. Dropout layer (Second Hidden Layer)

- The dropout rate is 20%.
- The purpose of this is to further regularize the network and prevents co – adaptation of neurons.

#### 5. Output Layer

- This single neuron is used with sigmoid activation function which gives output between 0 and 1
- Since this is a binary classification problem the sigmoid is ideal for threshold-based decision making.

### 5. Evaluation

- In this evaluation phase of CRISP-DM the model was assessed using metrics like accuracy, precision, recall and F1-score.
- Accuracy and loss curves along with a confusion matrix, were generated to visualize performance trends.
- From this result we confirmed that the model meets the objectives of classifying lithium battery related incidents with sufficient reliability.

### 6. Deployment Considerations

- Although the model is not yet deployed in a live system, the trained model can be integrated into fire incidents management tools or making dashboard for real-time classification of lithium battery fires. Its lightweight architecture allows for easy integration in cloud or local systems.

- The model can also be retrained regularly as new incident data becomes available, improving accuracy and adapting to evolving EV fire risks.
- This makes it suitable for practical use by emergency services for early risk dictation and faster response.

## EVALUTION / RESULT

To evaluate the performance of our deep learning-based fire risk classification model, we employed both the quantitative metrices and visual diagnostic tools. The central question was whether the model could accurately predict lithium-ion battery related fire incidents using structured attributes like ignition source, vehicle type and power system.

We have trained the model using a binary cross-entropy loss function and the Adam optimizer, with early stopping and dropout layers to mitigate overfitting. The dataset was split into training (64%), validation (16%) and testing (20%) ensuring balanced representation. The ANN was trained with the 50 epochs, with performance tracked across epochs.

To evaluate the model, we have created a classification report. From this report we acquired Accuracy of 84.76%, Precision of 82%, Recall of 81%, F1-Score has 81%. From this result we can state that the model performs strong with balanced class prediction, which is critical in high – risk contexts.

### Visualization

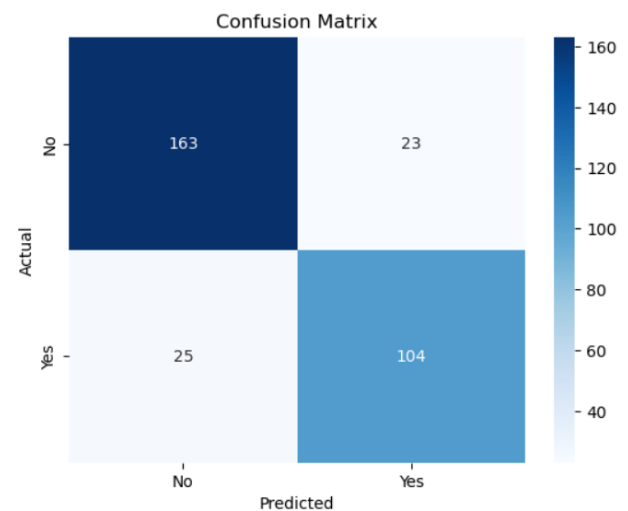
To evaluate the performance of the trained Artificial Neural Network (ANN) we have visualization techniques.

- **Confusion Matrix**

The confusion matrix illustrates how well the model distinguished between fire incidents involving lithium- ion batteries and those that did not.

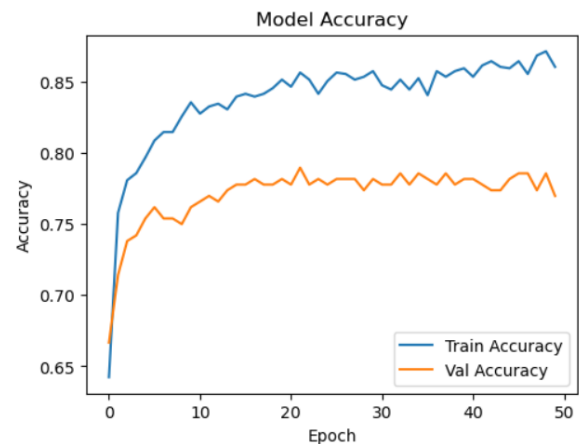
The model correctly classified 163 out of 186 non-battery incidents and 104 out of 129 battery related incidents.

Misclassification was relatively balanced (23 false positives and 25 false negatives), indicating no significant bias towards either class.

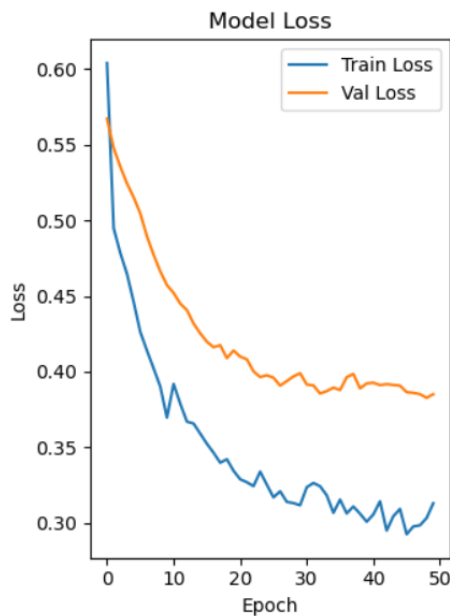


- **Accuracy and Loss Curves**

The training and validation accuracy and loss curves provide insights into model learning and potential



Accuracy gradually increased and plateaued with the training accuracy reaching 87% and validation accuracy 78 – 80 % indicating solid generalization performance.



From the above figure we can see that the training and validation loss steadily decreased, further confirming that the model was learning meaningful patterns without overfitting.

- Quantitative result

Metric	Value
Accuracy	84.76%
Precision	82%
Recall	81%
F1-Score	81%

These metrics highlight that the ANN is both precise and sensitive to detecting battery- related fire incidents.

### CONCLUSION

This study presents a deep learning based predictive model to identify lithium-ion battery fire incidents using structured emergency report data from the London fire brigade. By adopting CRISP-DM methodology and developing a feedforward Artificial Neural Network (ANN) we achieved a test accuracy of 84.76% which states that it has strong classification capability.

The primary contribution of this research lies in shifting fire risk assessments from post incident analysis to proactive

classification, which will help in emergency responses teams. Additionally, this approach offers scalability and can be retrained with new data as electric vehicle adoption increases.

However, the Study has limitations. The model was trained solely on categorical data and lacks real -time or sensor based information which could enhance prediction granularity. Also, interoperability remains limited compared to rule-based systems, and model’s deployment readiness was not evaluated in a live environment.

### FUTURE WORK

If more time and resources were available, several enhancements could be implemented.

- Integrate time-series sensor data for real time risk prediction.
- Add explainability using tools like SHAP or LIME to interpret model decisions.
- Deploy as a dashboard for fire services.

In summary, this work demonstrates the feasibility and value of using deep learning to classify lithium battery fir risks from structed incident data offering a steppingstone toward smarter, AI driven safety solutions in the electric mobility era.

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