Enhancing Forest Fire Predictions using Machine Learning and Deep Learning

MSc Research Project
MSc in Data Analytics

Madhumitha Arunkumar
Student ID: 23104678

School of Computing
National College of Ireland

Supervisor: Dr. Catherine Mulwa

National College of Ireland

MSc Project Submission Sheet

School of Computing

Student Name:	……. Madhumitha Arunkumar….………………………………………………………
Student ID:	………23104678…………………………………………………………………….……
Programme:	………MSc. In Data Analytics……………………….… **Year:** 2023-2024...
Module:	………MSc Research Project…………………………………………………….………
Supervisor:	………Catherine Mulwa …………………………………………………………….………
Submission Due Date:	………02/09/2024……………………………………………………………….………
Project Title:	………Enhancing Forest Fire Predictions using Machine Learning and Deep Learning……………………………………………………………….………
Word Count:	……………7892……………… **Page Count**……………22……………………….……..

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.
ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature: ………Madhumitha Arunkumar……………………………………………………………

Date: ………02/09/2024……………………………………………………………………………

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST

Attach a completed copy of this sheet to each project (including multiple copies)	□
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	□
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	□

Assignments that are submitted to the Programme Coordinator Office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Enhancing Forest Fire Predictions using Machine Learning and Deep Learning

Madhumitha Arunkumar
23104678

Abstract

Global climate change is causing more frequent and severe wildfires, posing major risks to both ecosystems and human populations. Traditional prediction techniques find it challenging to accurately predict wildfire dangers due to the dynamic nature of environmental elements. This problem is addressed in this study by utilizing advanced machine learning and deep learning techniques such as ResNet50, LSTM, and RBF Kernel SVR to enhance wildfire forecasting and identification. The research reveals that these models outperform older methods, with ResNet50 achieving 80.16% accuracy in analysing aerial images and LSTM models reaching 99.19% accuracy in detecting smoke in real-time. These results indicate that integrating these advanced techniques leads to more precise forecasts and improved wildfire management strategies, resulting in enhanced prevention and response measures in practice. This study advances current wildfire prediction methods by demonstrating how deep learning models can effectively capture intricate environmental patterns.

1 Introduction

Wildfire is dangerous to the integrity of the forest and the inhabitants of the forest because it affects the bearing of woods and lives of human beings, limitation of species diversification and sustainability of the ecosystem. This Research focuses on advanced prediction techniques which embedded deep learning and machine learning techniques to enhance the accuracy of risk prediction of the forest fires. Specifically, the purpose of this research is to obtain a stable forecast using climate data and other fire detection data from IOT and sensor devices that may help eliminate or at least slow climate change, as well as control forest fires.

1.1 Background and Motivation

The rise in severe weather patterns due to global climate change has led to a higher occurrence and greater intensity of wildfires, presenting considerable dangers to individuals, properties, and the variety of species. Traditional prediction methods have been unsuccessful in accurately forecasting the risk and behaviour of these fires because of the fluctuating weather patterns. Thus, this work is aimed at solving this critical issue by developing better prediction models by employing deep learning and machine learning approaches. This means that these models can assess big data and designing patterns of climate information which makes the forest fire predictions more accurate. The goal is to enhance strategies for controlling fires and managing forests to reduce the damages that may be caused by global climate change to the forests and the communities that depend on them. The study seeks to determine whether the use of deep learning techniques offers superior predictive capability for forest fire risks compared to traditional meteorological approaches that enhance effective wildfire prevention measures.

1.2 Research Questions, Objectives and Contributions

Research Question: How can advanced machine learning and deep learning models, utilizing climate data, be optimally developed and applied to accurately predict forest fire risks and intensities under the changing conditions of global climate change and how can these models inform and enhance strategies for wildfire prevention and forest management?

The Sub Research Questions are:

Sub.RQ1**:** How effective are IoT, sensor device data and aerial Images in detecting forest fires and assessing their intensity?

Sub.RQ2**:** Which machine learning or specifically which deep learning algorithm is the most accurate and reliable one for a given problem.

Research Goals:

The primary purpose of this research is to establish a prediction model for the forest fire risk using deep learning and machine learning approaches. The specific goals are:

- To identify the main causes of forest fires by analysing historical climatic data.
- To implement and compare various Machine Learning & Deep Learning methodologies like Radial Basis Function Kernel (SVR), ResNet, LSTM, RNN, GAM, and XGBoost, to evaluate how well they can forecast the risk of forest fires.
- To deliver the purpose of facilitating policy analysis regarding the efficient forest fire management as influenced by the results of the predictions

Research Objectives:

To address the above Research Questions and Approach, the Project Objectives were developed and implemented as shown in Table 1.

Table 1. Research Objectives

Obj.	Objectives	Models	Evaluation
1	A comprehensive analysis of existing research on how climate change influences forest fires		
2	Exploring the methodology, detailing on data collection, preprocessing steps, and the selection of models.		
3	Implementation, Evaluation and Results of Forest Fire Prediction and Management		
3. 1	Implementation, Evaluation and Results of Forest Fire Area Analysis	GAM, SVR (RBF Kernel), XgBoost	MSE, RMSE
3. 2	Implementation, Evaluation and Results of smoke detection using IOT and sensor devices analysis	RNN(LSTM)	Classification Report, Confusion Matrix
3. 3	Implementation, Evaluation and Results of Aerial Imagery analysis	ResNet, LSTM	Confusion matrix, AUC – ROC curve
4	Comparison of Developed Models (Obj.3)		
5	Comparison of Developed Models (Obj.4) with Existing models		

The remaining part of the report is organized as follows: Section 2 provides a comprehensive literature review, analyzing previous studies on forecasting forest fires using machine learning and deep learning approaches. Section 3 offers a thorough description of the research methodology, including data collection, preprocessing, and model selection. Section 4 discusses the design specification, detailing how the models are implemented. Section 5 discusses the implementation, evaluation, and results, providing a detailed analysis of the models' outcomes. Section 6 provides a comparison of developed models and evaluates their results in relation to current studies, highlighting advancements and contributions. Finally, Section 8 of the report concludes the study and offers potential suggestions for future work.

2 Literature Review

2.1 Introduction

The frequent occurrence and intensity of forest fires have increased significantly hence increasing the need for accurate modeling and timely identification of wildfires. This chapter provides a literature review of the prior studies on the prediction and management of forest fires through ML and DL techniques. Therefore, the application of new technologies such as ResNet50 and LSTM models are considered as the leading approach to enhance the prediction proficiency and decrease hazardous factors associated with forest fires. It begins by discussing how these models have developed, with the change from traditional methods to deep learning, and revisits significant work that has applied CNNs, transfer learning and data augmentation to enhance the detection rate. The review also delves deeper into the application of climate data in predictive modeling; for instance, analysing how various climatic factors are incorporated into models including LSTM networks, with the aim of improving on the propensity of fire risks. It also deliberates on the application of remote sensing and IoT techniques for real-time monitoring and management of fires along with the associated benefits and limitations. The review ends by evaluating the influence of the predictive modeling on forest management highlighting the importance of models that are accurate in real-world conditions to be practical as well. In the present literature review, the current state of research in this specific field is thoroughly examined and analysed and crucial advancements are identified as well as shortcomings; this analysis puts into perspective the proposed study.

2.2 Critical Review of Climate Data in Forest Fire Prediction

Climate is a major central control variable in case of forest fires as variations of temperature, humidity, and wind help in assessing the probability of fire. (Priya & Vani, 2023) study, AIM is applied to design different approaches to use climate change predictions to estimate the incidence rate of forest fires in the following years in deep learning models. This work seeks to determine the correct temperature prediction in relation to potential fire risks using the ARIMA model together with other models like logistic regression model and the random forest model This here work incorporates the deep learning application for high accuracy within these models. However, having compared their results with a large number of climatic variables determining risks of fire, this approach has certain shortcomings related to the application of elementary architectural models that do not adequately interpret subtleties of climatic conditions in various regions. Therefore, more research into such machines learning models as the LSTM networks and CNNs is required for them to be created. They are helpful in enhancing precision and relevance of fire risk prognosis in diversified territorial and meteorological conditions. Moreover, the first research offers a relatively scant discussion about how these models can be adjusted depending on the characteristics of the environment – a factor being critical for understanding general and stable forecasting methods.

2.2.1 Research Enhancement

The previous work "Climate Change Forecast for Forest Fire Risk Prediction using Deep Learning" by Priya and Vani (2023) employs both ARIMA and basic deep learning techniques while failing to determine the possibilities of a variety of architectural models. In a bid to fill these gaps, this research seeks to use more complex deep learning structures such as LSTM and or CNNs. Complex models may also incorporate temporal and spatial dependencies inherent in climate variables yielding a more accurate and fine-grained measurement of the risks of forest fires. It is also significant to extend covered model types to embrace all types of models that can bring a better understanding of factors determining climate-related events predictability. Furthermore, this research seems to dismiss some of the proposed models while paying insufficient attention to how these models may be implemented in various geographical regions or under particular climatic conditions. In addressing this research question, this project compares the performance of the developed models across different environmental contexts to come up with general solutions. In addition, the quality and quantities of the data set need to be assessed in detail. Correction of biases or missing information relating to climatology enables improvement of the validity and reliability of models. Thus, by using this highly integrated approach, the validity of the research outcomes can be deemed high for various scenarios, hence, contribute to the development of the climate change and forest fire risk forecasting area.

2.3 An Investigation of Wildfire Detection and Prediction Models

A shift from traditional approaches to advanced deep learning techniques has been observed in the development of wildfire detection and prediction models. (Reis et Turk., 2023) improved forest fire detection accuracy by incorporating deep convolutional neural networks (CNNs) with transfer learning, making a significant contribution. Their approach, which relied on the use of pretrained models and a huge volume of data, produced more accurate results in the identification of fire incidents when the environment is intricate. However, there is a possibility of restrictions when depending only on transfer learning because existing models might not understand the peculiarities of each region. However, their approach had the capacity to detect fires but lacked the features that are useful in predicting and preventing fires. On the other hand, (Sousa et al. 2020) paid more attention to improving datasets to improve the training of the detection model. These data sets were then further expanded on as an application of transfer learning to enhance the robustness of the model. Although this method was helpful in dealing with the issue of having sparse data it was resource hungry, and this was a major drawback when it comes to real time application. Both studies underline the importance of data-driven methods but highlight a common challenge, the requirement for models that are both highly accurate as well as efficient for real-time computations.

2.4 Machine Learning Approaches in Forest Fire Prediction

Advanced approaches of machine learning algorithms have played a greater role in the improvement of forest fire predictors in terms of reliability and usefulness. (Pang et al., 2022) employed random forest (RF) and gradient boosting machine (GBM) in machine learning to forecast forest fires from meteorological data. In their model, they proved to be particularly proficient in determining complicated correlations between variables, including temperature, humidity, and wind speed, which are important for evaluation of fire hazards. Nevertheless, the model's reliance on accurate weather information means that in areas with poor or uneven information, it is not very adaptable. This research is useful in showing how machine learning benefits the analysis of large environmental data sets; however, cautionary measures should be taken when constructing models with limited information.

2.5 A Review of Remote Sensing and IoT in Forest Fire Management

The combination of remote sensing data and Internet of Things (IoT) devices has transformed the monitoring and management of forest fires. (Guan et al., 2022) used a better instance segmentation model to distinguish forest fires from aerial imagery, demonstrating the efficiency of remote sensing in monitoring fires immediately. Their method enhanced the accuracy of detecting and monitoring fires which are imperative in controlling fires. However, the model has shortcomings in areas where or where it is hard to get such high-quality aerial images, which are basic in the model. In (Dewangan et al., 2022), SmokeyNet, an instant smoke detection model designed using deep learning characteristics and remote sensing data, was presented. This model is exemplary in providing the necessary output in real time towards early prognosis and control. However, this model may not work well during the presence of fog or cloud since they may be misinterpreted as smoke. The present research helps to widen the understanding of applying real-time fire detection while emphasizing the need for models that could classify similar visual patterns in various contexts.

2.6 Predictive Modeling and Forest Management

The use of predictive modeling in planning and management of the forest and the formulation of policies has major consideration. In (Gao et al., 2023) study, authors utilized the Random Forest algorithm as well as Backpropagation Neural Networks to forecast fire risks in Heilongjiang Province, China. Their model was useful in identifying areas that were most prone to fire, hence helpful in resource utilisation. However, there are many assumptions used to come up with the model and these may reduce the model usability for the forestry managers who are interested in simple models that can easily be used. This research suggests a focus on creating predictive models that the practicing professional will embrace in clinical practice. (Wu et al., 2022) used Artificial Intelligence propositions to analyse a Forest fire spread pattern. This is important for increasing fire control measures since they help in the evaluation of various approaches and measures. However, dependencies between various factors and their correlation affect the results of these simulations depending on the place and conditions where this input data is collected. It is useful for the understanding of fire management and the decision-making processes tied to it but as observed the problem of data reliability can occur across various situations.

2.7 Comparison of Existing Techniques and Drawbacks

Table 2 gives a summary of research using advanced techniques for managing forest fires, showcasing the benefits and drawbacks of each method and suggesting ways to improve or integrate them for better fire management strategy.

Table 2. Comparison Table of the literatures

Title	Author	Focus	Techniques	Results	Drawbacks
Forest Fire Prediction and Management	Wu et al. (2022)	Comparison of LSTM and ResNet models for fire spread prediction.	LSTM, ResNet	LSTM: 85%, ResNet: 78%	LSTM struggles with complex spatial relationships; ResNet have lower temporal accuracy.
Remote Sensing and IoT in Forest Fire Management	Guan et al. (2022)	Real-time fire monitoring using remote sensing and IoT	SmokeyNet for smoke detection	SmokeyNet: 92%	Reliance on high-quality aerial imagery; potential misidentification due to weather conditions
Comparative Study on Climate Data	Pang et al. (2022)	Comparative investigation of ResNet50 and LSTM for predicting forest fire risks.	ResNet50, LSTM	ResNet50: 82%, LSTM: 87%	Requires high computational resources; models cannot generalize well to different regions.
Deep CNN for Forest Fire Detection	Reis and Turk (2023)	Improving fire detection accuracy using CNNs and transfer learning	CNNs with transfer learning on pre-trained models	CNN: 90%	Limitations in adapting to unique geographical features
Historical Climate Data Analysis	Priya & Vani (2023)	Association of global temperatures with forest fire frequency and intensity.	ARIMA, Basic Regression	ARIMA: 70%	Lower accuracy due to inability to capture complex temporal and spatial features.

2.8 Conclusion

Even though there have been advancements in creating predictive models for forest fire detection and management, there are still various obstacles to overcome. Existing models, despite being sophisticated, frequently face challenges in terms of scalability, applicability across different regions and climates, and real-time implementation. The combination of different data sources, including climate data, remote sensing, and IoT, has enhanced model accuracy while also bringing about challenges that may impede practical application. There is a definite requirement for models that achieve a balance between accuracy and simplicity, ensuring they are effective and accessible for practical application. This study suggests creating a strong, expandable forecast model utilizing deep learning and machine learning methods, with a focus on enhancing versatility and immediate application in various settings. This research seeks to improve forest fire management strategies effectiveness amidst climate conditions that are becoming more unpredictable by addressing these gaps.

3 Research methodology

The methodology section describes the overall approach for all 3 datasets used in this project to predict forest fires systematically. This includes everything from collecting and preprocessing data to more complex tasks like advanced machine learning and deep learning. Every tool used in different stages of the process is detailed, including explanations of calculations made during data transformation and the assumptions that drive these transformations. A detailed framework for each analysis will be discussed in section 3.2 for better understanding.

3.1 Forest Fire methodological approach

The framework chosen for conducting this study is CRISP-DM because of its structured and iterative approach as illustrated in Figure 1. This approach in the methodology guarantees that each phase of the project is well thought out and implemented thus yielding high credibility and validity of the outcomes. Its ability to accommodate all the phases for business and deploy them for different projects with varying sets and purposes makes it a flexible approach. This research centered on three main objectives: classifying aerial wildfire images with ResNet50, modeling the forest features to predict the impact of wildfire with traditional ML models, detecting the smoke with data from IoT devices and studying their results. Each of these tasks was designed with the purpose of enhancing precision, as well as speed, of devices applied for the detection of fire in the forests and the anticipation of such occurrences. To be responsive to the dynamics of other associated researches on similar topics and to determine the right approach for this study,a review of literature was conducted.

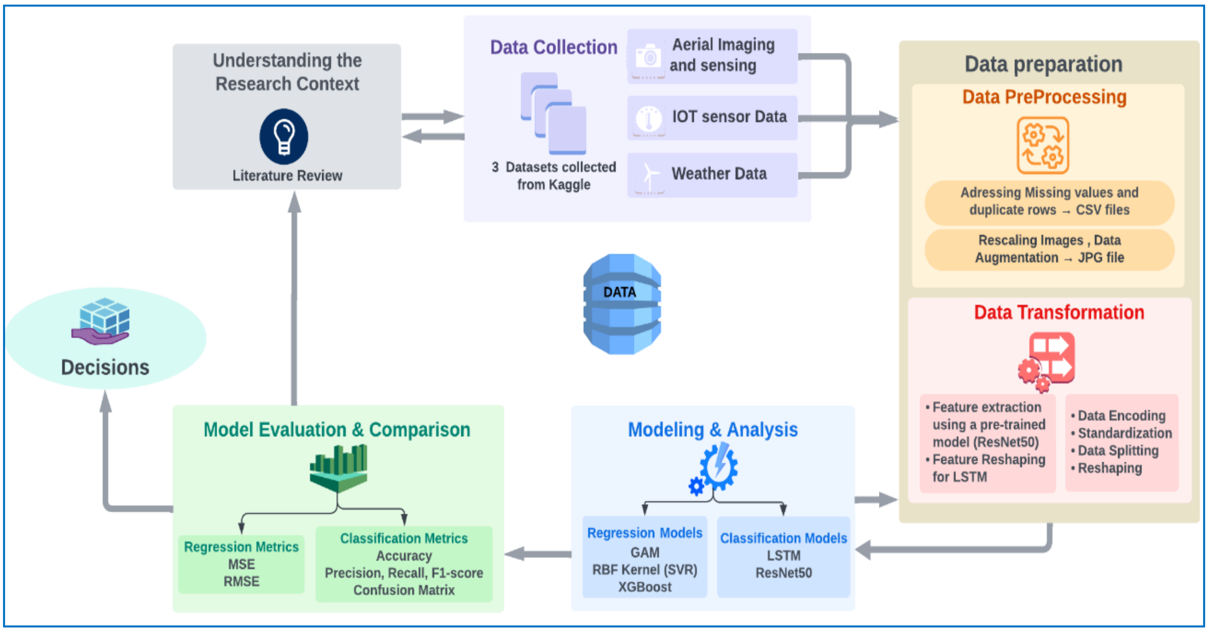

Figure 1. Forest Fire Methodology Approach

3.2 Data Collection

There different Data was sourced from Kaggle, offering a varied and extensive dataset crucial for thorough model training and assessment. The datasets that were utilized are as follows:

- **Smoke Detection Dataset:** This data includes different sensor data from the environment, which is important for the binary classification of smoke detection. This dataset contains 62630 entries providing information on temperature, humidity, and additional environmental variables.
- **Factors Influencing wildfire dataset:** This dataset provides information about diverse types of forests, their characteristics, and various environmental factors. It offers a comprehensive view for analyzing forest conditions and patterns across different regions.
- **Aerial imagery and sensor dataset:** A collection of aerial images showing wildfires, utilized for tasks like image classification to detect and track wildfire events through aerial photography. The dataset contains 3670 pictures, amounting to roughly 5 GB in size.

3.3 Data preparation

This section explains the detailed flow of the methodological approach according to the implementation of each dataset, their analysis, and data preparation methods undertaken. Each dataset is carefully analyzed based on its unique qualities and our research needs as shown in Figure 2. These customized measures ensure that every dataset is properly prepared to help improve our goal of enhancing wildfire detection and prediction abilities. Preparing data is vital to ensure datasets are appropriate for modeling and analysis.

3.3.1 IOT Smoke Detection Dataset

Smoke Detection data undergoes initial preprocessing, starting with aligning sensor timestamps for time consistency. Next normalization is done, where the data is scaled to a common range, improving the reliability and efficiency of machine learning models. The processed data is reshaped for input into a Recurrent Neural Network (RNN).

3.3.2 Factors Influencing wildfire dataset

In the same way, the Forest Fire Influencing Factors Dataset undergoes data cleaning to eliminate noise and irrelevant information, categorical variables like 'month' and 'day' are encoded numerically and then moves on to normalization for ensuring feature consistency. Subsequently, this data is utilized for the training of machine learning algorithms

3.3.3 Aerial imagery and sensor dataset

The Aerial Image Dataset uses a pipeline specific to images, resizing them for consistency and eliminating noise to enhance model precision (Park et al., 2021; Guan et al., 2022). Techniques such as flipping, rotation, and scaling are used to boost dataset variety and improve the resilience of the model. Augmented images are utilized for the training and testing of a ResNet50 model. Throughout these processes, exploratory data analysis and visualizations help in understanding data relationships, ensuring the datasets are clean and ready for model training

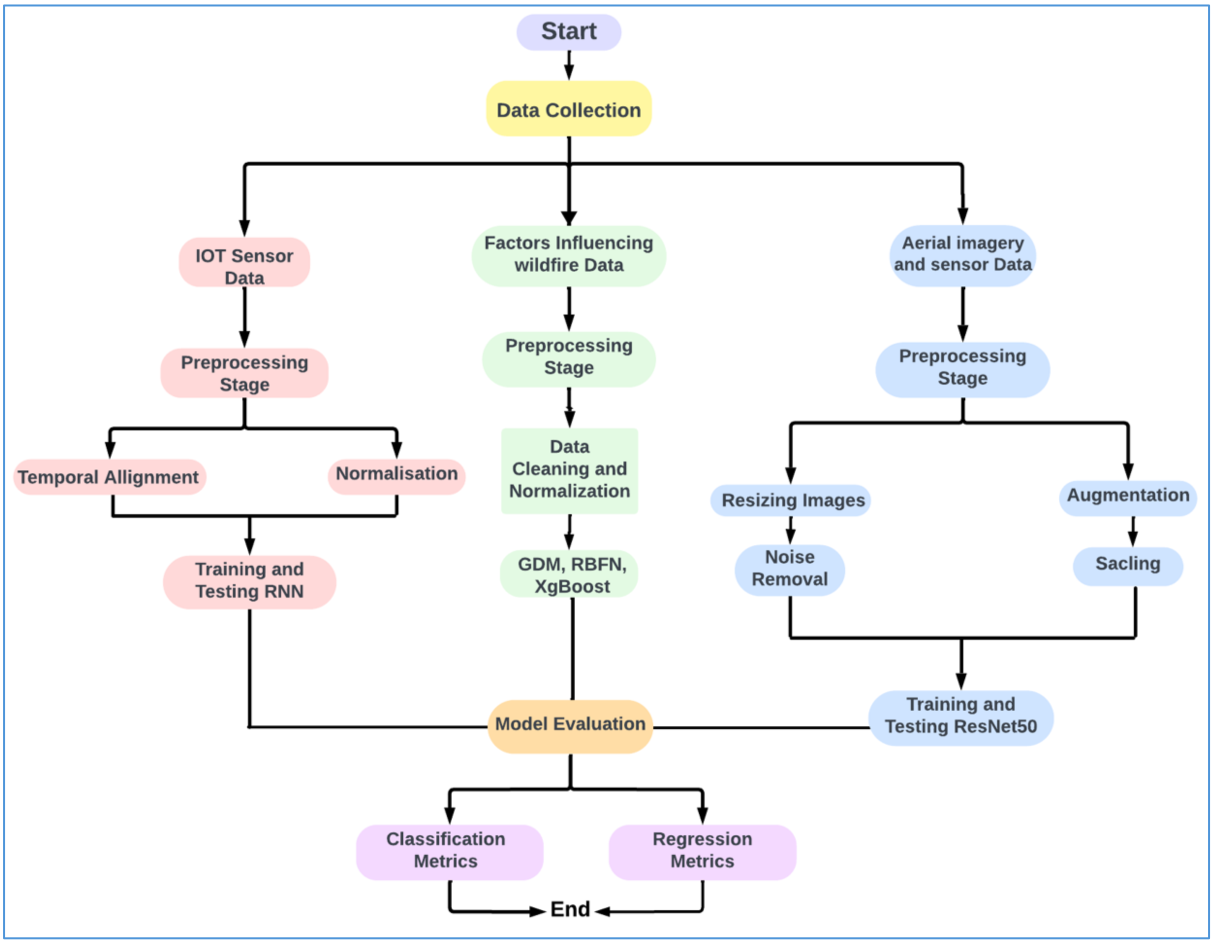

Figure 2. Overall Flow of the Analysis

3.4 Modeling and Analysis

The modeling and analysis phase includes using advanced machine learning and deep learning methods to make accurate predictions and classifications regarding forest fires and smoke detection. To predict the size of burned areas, regression models such as Generalized Additive Models (GAM), Support Vector Regressors (SVR) with RBF kernels, and XGBoost models are utilized (Gigović et al., 2019; Li et al., 2024). An LSTM-based Recurrent Neural Network (RNN) is developed for smoke detection using IoT sensor data. This model analyzes sequential data to anticipate the occurrence of smoke and is trained and validated using early stopping to prevent overfitting. The pre-existing ResNet50 model is used to process aerial image data for tasks related to image classification. This model has been adjusted with extra dense layers to improve its precision in identifying wildfires from images. The ResNet50 model is employed to extract features, which are then inputted into an LSTM model for further analysis.

3.5 Evaluation

The performance of the classification model is assessed using accuracy, precision, recall, F1 score, and confusion matrix to achieve high accuracy in fires and smoke identification. mean squared error (MSE) and root mean squared error (RMSE) are used to evaluate the prediction accuracy of models such as: GAM, SVR with RBF kernel, and XGBoost. The different regression models are then compared in an attempt to select the one best suited for burnt area estimation.

4 Design Specification

The implementation process consists of three stages: Data Preparation, Data Modeling, and Evaluation as shown in Figure 3

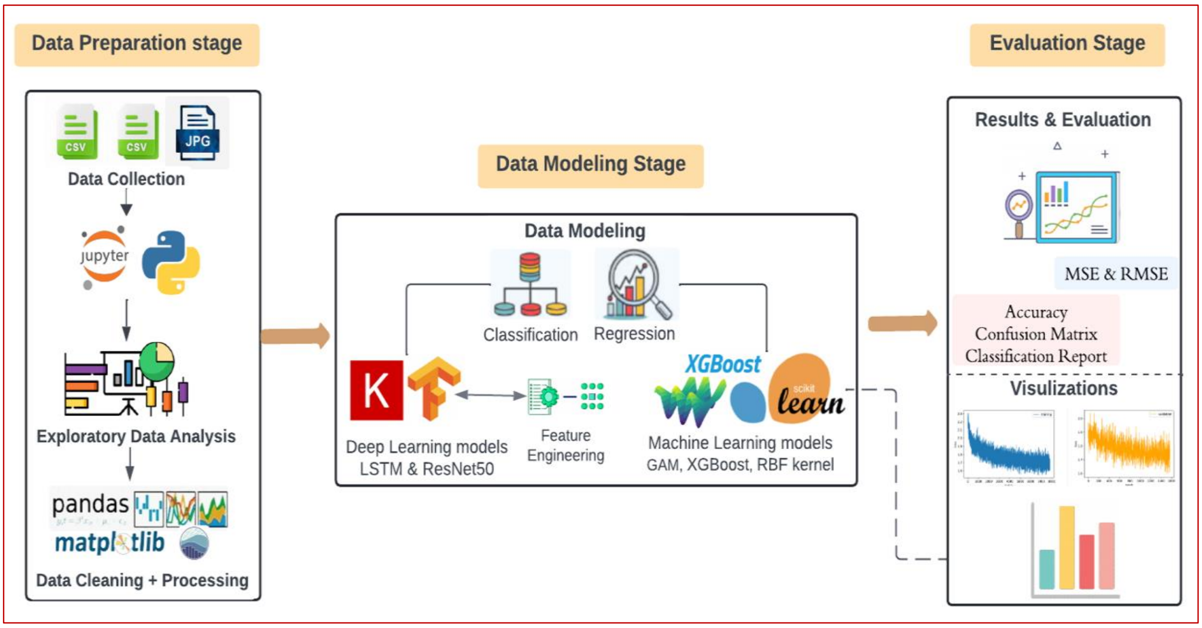

Figure 3. Design Framework

Data Preparation Stage begins by collecting data, including gathering datasets such as CSV files and images. Exploratory data analysis (EDA) is then performed to find patterns and trends for each data after it is collected. Data cleaning and processing are conducted to manage missing values, resize images, convert data to a consistent format, and normalize it, ensuring the dataset is error-free and ready for high performance in subsequent stages.

Data Modeling Stage includes various critical processes, encompassing both classification and regression tasks. Traditional machine learning models such as Generalized Additive Models (GAM), XGBoost, and Radial Basis Function (RBF) kernels are implemented for the regression analysis with Factors Influencing wildfire data. Deep learning models like Long Short-Term Memory (LSTM) networks, RNN and ResNet50 are implemented for Aerial images and smoke detection data, respectively. Feature engineering is first applied to a pre-trained deep learning model, specifically ResNet50, reshaping it into LSTM for processing the image dataset.

Evaluation Stage is crucial for evaluating the models created in the previous stage. This is done using different metrics like MSE, RMSE, accuracy, confusion matrices, and classification reports. Automation of the evaluation process includes visualization through plots and graphs based on predictions and management.

In conclusion, the implementation is designed to support both traditional machine learning and deep learning approaches, ensuring a flexible, modular pipeline that can be adapted to various tasks.

5 Implementation, Evaluation and Results of Forest Fire Prediction and Management

5.1 Introduction

This chapter summaries the implementation, Results and evaluation of the models used to Predict and manage wildfire. Figure 2 depicts a thorough data analysis procedure that includes three separate datasets: The Internet of Things Sensor Data, the Influencing Factor Dataset and the Forest Fire Image Dataset. The process of data analysis is carried out in a structured manner that when analyzing every dataset, there are some common procedures that are followed including preprocessing, modeling, and evaluation procedures. The aim of all this remains to use methodologies such as Machine learning & more specifically Deep learning methods to extract useful information or make predictions from the data.

5.2 Implementation, Evaluation and Results of Forest Fire Area Analysis

5.2.1 Implementation

This is a regression analysis that is conducted with the help of all the factors which led to the causation of forest fire and all the burnt area. In this Analysis, three models were employed: the application of Generalized Additive Models (GAM), Support Vector Regressor (SVR) using radial base function kernel and XGBoost. And after the categorical variables encoding and all the features scaling it is split into the training and the test sets, at the ratio of 8 to 2. The GAM is then refitted using 'LinearGAM' class in python's pygam' to model the non-linear relationship between the predictors and area in the training data. The difficult non-linear relation is captured by the SVM model as introduced using 'sklearn's SVM with an RBF kernel. Finally, the XGBoost model is created by using 'XGBRegressor' provided in the 'xgboost' package that is able to handle different interactions between the features and prevent overfitting. Every part of the model's output was assessed for decision.

5.2.2 Evaluation and Result

These models were assessed with the test set, focusing on metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) as this is a regression analysis. The RMSE of 111.40 from the GAM showed that it could predict forest fire area with reasonable accuracy by capturing its variability. The SVR using an RBF kernel slightly surpassed the GAM, with an RMSE of 110.12, indicating its superior ability to handle the data's nonlinear characteristics. In the end, The XGBoost model resulted in an RMSE of 111.71, close to that of the GAM, showing strong predictive performance but slightly underperforming compared to the SVR. Table.3. clearly shows the evaluation metrics for each model, providing a comparison of their predictive performance.

Table. 3 Evaluation metrics of Regression model

Models	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)
Generalized Additive Model (GAM)	12,409.63	111.40
Support Vector Regressor (RBF Kernel)	12,126.87	110.12
XGBoost	12,478.31	111.71

5.3 Implementation, Evaluation and Results of smoke detection using IOT and sensor devices analysis.

5.3.1 Implementation

The smoke detection analysis was conducted using a Recurrent Neural Network (RNN) model, specifically employing an LSTM (Long Short-Term Memory) network layer which is well-suited for time-series data (Guan et al., 2022; Dewangan et al., 2022). After preprocessing the dataset, some of the features presents were standardized using 'StandardScaler' to ensure that all features contributed equally to the model. The standardized features were then split into training and testing datasets with an 80-20% ratio. The data was further reshaped to meet the input requirements of the LSTM layer, where each sample was formatted into a three-dimensional array corresponding to the number of samples, time steps (set to 1), and features.

The model was implemented using Keras's Sequential API. The process started with a 50-unit LSTM layer, which was activated with the ReLU function to add non-linearity and assist the model in understanding intricate data patterns. This was followed by a dense layer with a sigmoid activation function to produce binary outputs, which produced a probability score indicating the likelihood of a fire alarm. The model was compiled using the Adam optimizer, known for its efficient handling of sparse gradients, and the binary cross-entropy loss function, appropriate for evaluating binary classification tasks. The model is trained on the training dataset for 50 epochs, with early stopping implemented to prevent overfitting, monitoring the validation loss and halting training if no improvement was observed for five consecutive epochs.

5.3.2 Evaluation and Results

The trained LSTM based RNN model was evaluated on the test set to determine its level of generalization (Dewangan et al., 2022). Progress of the model was tracked across 50 epochs, showing continuous improvements in accuracy and loss for the validation data. The model initially had an accuracy of 78.99% for the training set in the first epoch, while that of the validation set was 89.63%. After each subsequent epoch, better performance is realized. By the 50th epoch, this resulted in a very strong model capable of accurately classifying fire alarms. The model had a training accuracy of 99.08% and a validation accuracy of 99.19%. Moreover, at this stage, it has a validation loss of 0.0230, reflecting robust performance. The final test data validation confirmed that the model has good predictive capability, achieving as high as 99.19% accuracy. Strong metrics of accuracy and low loss indicate that this model has learned the most important patterns from the data and is reliable for practice in smoke detection.

The evaluation of the smoke detection model was conducted using several key performance metrics, including the classification report, confusion matrix, and visualizations of training and validation accuracy and loss over the epochs.

	precision	recall	f1-score	support
0	1.00	0.97	0.99	3594
1	0.99	1.00	0.99	8932
accuracy			0.99	12526
macro avg	0.99	0.99	0.99	12526
weighted avg	0.99	0.99	0.99	12526

Figure 4. Classification Report

The detailed breakdown of the model's performance across various classes is presented in the classification report, Figure 4. In the absence of a fire alarm in class 0, the model achieved a precision of 1.00, a recall of 0.97, and an F1-score of 0.99, using 3,594 instances in the test group. In class 1 (fire alarm), the precision, recall, and F1-score were all 0.99 each, with evaluation based on 8,932 instances. These metrics show that the model is very precise in predicting both classes, especially excelling in accurately recognizing fire alarms (class 1). The model's high reliability in detecting smoke and triggering the alarm correctly is reflected by the 99% overall accuracy on the test set. The precision, recall, and F1-score macro and weighted averages were all 0.99, indicating a consistent performance in both categories.

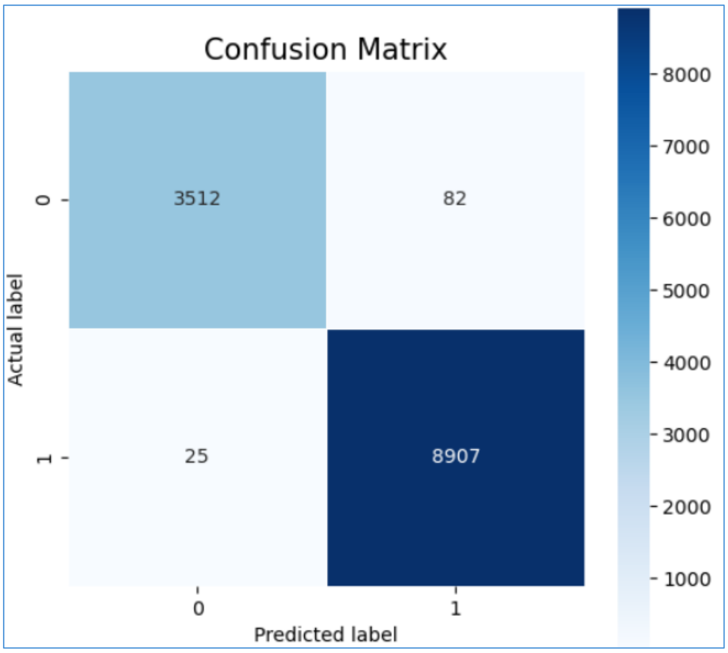

Figure 5. LSTM model Confusion Matrix

The confusion matrix provides additional insight into the predictive capabilities of the model. Figure 5 matrix shows that out of 3,594 instances where no alarm occurred, 3,485 were accurately predicted as no alarm, while 109 were incorrectly predicted as alarms. On the other hand, all 8,932 real alarms were accurately identified as alarms with no errors. This outcome highlights the model's outstanding ability to remember fire alarms, ensuring it rarely misses real fire events, which is vital for safety-critical tasks such as smoke detection during wildfire.

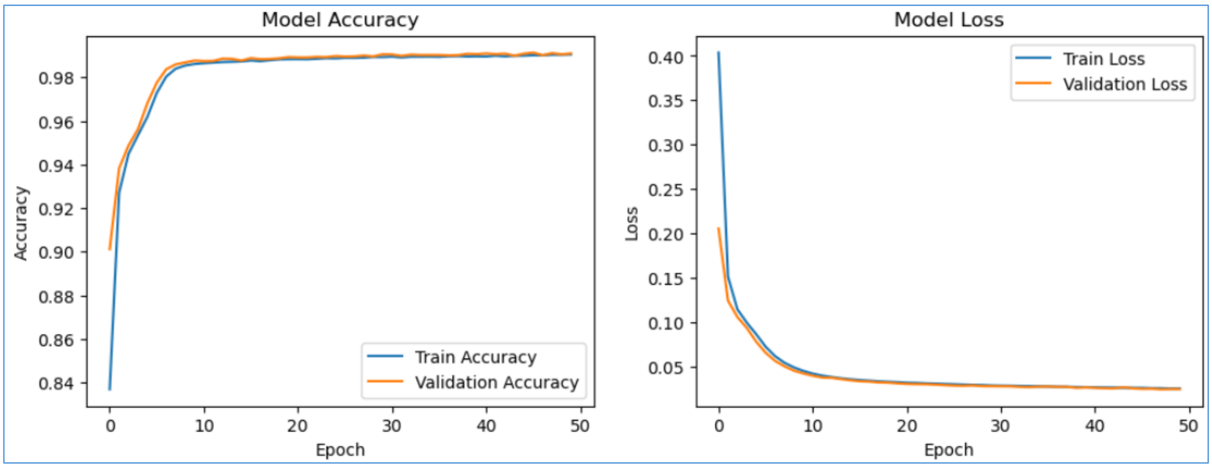

Figure 6. Learning curves of RNN(LSTM) model

To gain insights into the model's learning process, the training and validation accuracy and loss were plotted over the course of 50 epochs as illustrated in Figure 6. The charts demonstrates consistent progression in accuracy and loss with training accuracy climbing from 78.99% in the beginning epochs to exceeding 99% by the 50th epoch. The validation accuracy showed a comparable pattern, reaching 99.19% at the conclusion of the training period. The decreasing loss curves show that the model was effectively learning and generalizing without significant overfitting as both training and validation loss consistently decreased with parallel trends.

5.4 Implementation, Evaluation and Results of Aerial Imagery analysis

5.4.1 Implementation, Evaluation and Results of ResNet50

Implementation:

The process of implementing the model for aerial image analysis starts by utilizing the ResNet50 structure, a complex convolutional neural network already trained on the ImageNet dataset. ResNet50 is being utilized as a feature extractor by loading it without its final dense layers of the original model. The model's input shape is set at (224, 224, 3), a standard size for ImageNet-pretrained models. This is the setup for the base model. Following the loading of the base model, additional custom layers are incorporated on top of the ResNet50 base model for the specific binary classification objective. Initially, the ResNet50 output is flattened to convert the multidimensional tensor into a single dimension. Next, a dense layer with 1024 units and ReLU activation is included to bring in non-linearity, followed by a last dense layer with a single unit and a sigmoid activation to generate single output that is suited for binary classification result. To prevent overfitting and maintain the pre-trained weights, the convolutional base layers of the ResNet50 model are frozen. The Adam optimizer and binary cross-entropy loss function are used to compile the model, ideal for binary classification tasks. The model is subsequently trained on the aerial imagery data for two epochs, making use of data generators to streamline batch processing. The Binary Cross-Entropy (BCE) is calculated as follows:

$$\text{BCE} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \cdot \log(p_i) + (1 - y_i) \cdot \log(1 - p_i)\right]$$

To enhance the model's performance, fine-tuning is performed by unfreezing the layers of the ResNet50 base model, allowing the previously frozen layers to be updated during training. The model is recompiled with a lower learning rate (1e-5) to prevent large updates that could disrupt the pre-trained weights. The model is then trained for an additional epoch.

Evaluation and Results:

The evaluation of the implemented ResNet50 model on the aerial imagery data highlights the success of the approach, albeit with certain constraints. Initially, the model achieved a test accuracy of 67.45%, indicating that it effectively captured important spatial features from the aerial images, which are crucial for differentiating the two categories in the binary classification job. The learning curves for both accuracy and loss showed consistent improvements across epochs, with training and validation curves converging, suggesting good generalization and minimal overfitting. To further enhance the model's performance, fine-tuning was performed by unfreezing all layers of the ResNet50 model and recompiling it with a lower learning rate to ensure stable updates during training. After fine-tuning for an additional epoch, the model showed significant improvement, achieving a training accuracy of 80.16%. This demonstrates that fine-tuning allowed the model to leverage the deeper layers of ResNet50 more effectively, resulting in better performance on the aerial imagery dataset.

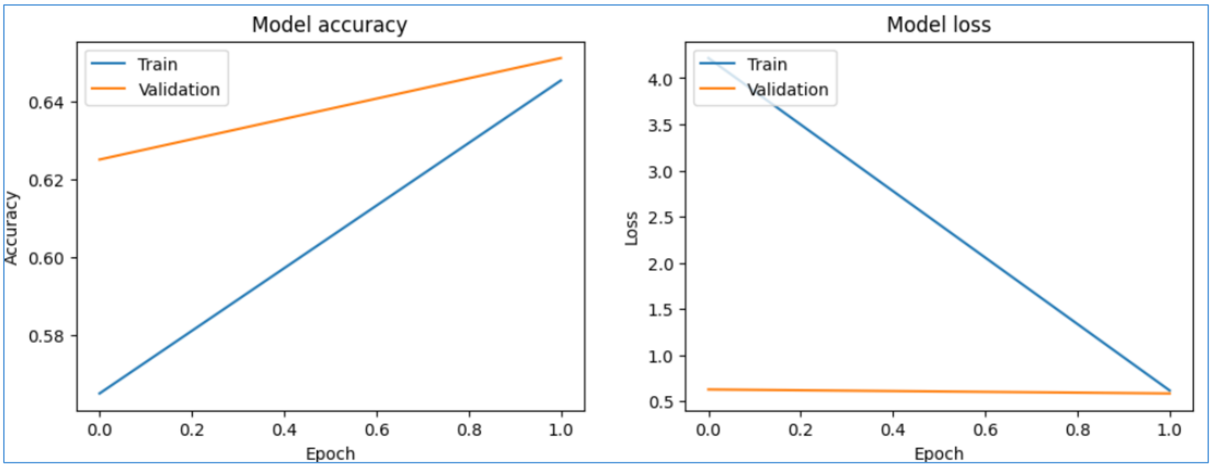

Figure 7. Learning curves of ResNet50 model

The learning curves displayed in Figure 7 reflect the training and validation accuracy and loss over 1 epoch. While the graphs indicate an overall upward trend in accuracy and a decrease in loss, which are promising signs of learning, the limited number of epochs provides only a glimpse into the model's potential performance. The sharp improvements seen in just one epoch made in finetuning suggest that with more extensive training supported by better system configurations, the model could achieve even more significant gains.

5.4.2 Implementation, Evaluation and Results of LSTM

Feature Extraction from ResNet50:

The implementation began with feature extraction from the pre-trained ResNet50 model, which was used to extract features from the input aerial imagery data. ResNet50, a deep convolutional neural network pre-trained on the ImageNet dataset, was employed while retaining only its convolutional layers (include_top=False). The feature extraction process involved passing the images through ResNet50 to obtain feature maps with dimensions of 7x7x2048 for each image, representing spatial features crucial for the subsequent LSTM model. A customized function was created to retrieve these features from the training, validation, and test sets. The features were reshaped after extraction to fit the LSTM model, converting each 4D tensor (samples, 7, 7, 2048) feature map to a 3D tensor (samples, 49, 2048). This transformation was necessary to adjust the data to match the expected input format of the LSTM, which analyzes sequences of feature vectors.

Implementation:

The extracted features were inputted into an LSTM model created for binary classification. The goal of the LSTM model was to understand sequential and spatial patterns in the features. The structure included two LSTM layers with 256 units each, with the first LSTM layer outputting sequences for the second LSTM layer to analyze the full sequence. Dropout layers were added after every LSTM layer to avoid overfitting by randomly dropping units while training, thereby improving the model's capacity to generalize unseen data. The final layer of the model utilized a sigmoid activation function to generate a likelihood score for the binary classification objective. Similar to the ResNet50 model, the LSTM model was built using the Adam optimizer and binary cross-entropy loss function. The model underwent three training epochs using the training data, followed by validation on the validation set after each epoch. Tracking the accuracy and loss for both training and validation sets, the learning process was closely monitored. The results in those time periods saw improvements but the process was gradual, resulting in a final test accuracy of 61.22%.

Evaluation and Results:

The LSTM model's accuracy on the test dataset was lower than that of the ResNet50 model. The test accuracy of the LSTM model was about 61.22%. While the LSTM model was initially expected to enhance performance by capturing temporal dependencies, the results indicate that this approach may not be optimal for analyzing the fixed spatial attributes present in aerial images. The intricate nature of these spatial characteristics may prove difficult for the LSTM model to effectively analyze, as it is specifically built to manage temporal relationships instead of stationary arrangements. The LSTM model's learning curves from Figure 8 illustrates consistent loss values with relatively low accuracy during training and validation, suggesting challenges in optimizing the model for this task. The findings indicate that although the ResNet50 model did well, the LSTM model might need additional modifications or a different method to accurately identify and interpret the spatial patterns found in aerial images.

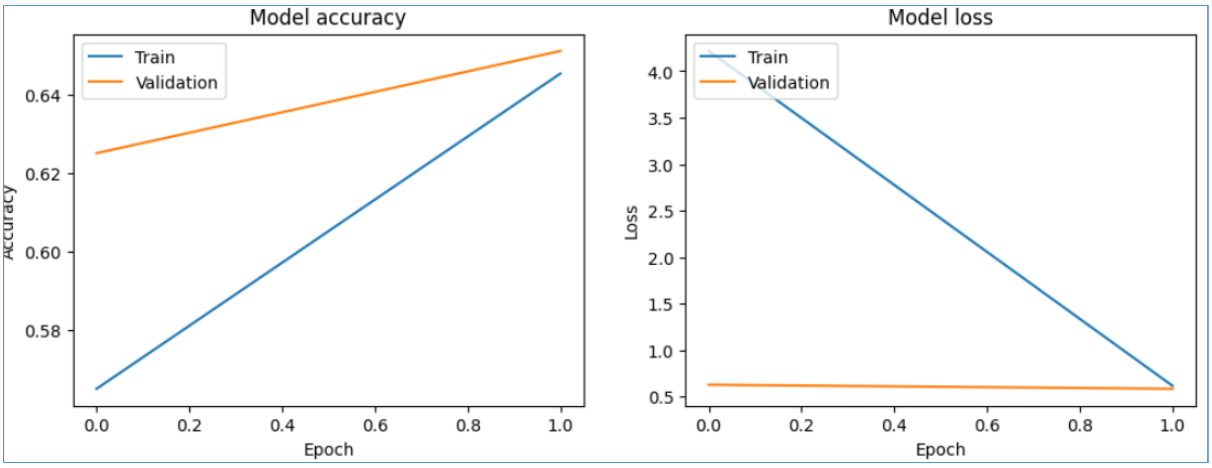

Figure 8. Learning curves of LSTM model

6 Comparison of Developed Models and Discussion

This section provides a detailed comparison of various implemented models assessing their effectiveness in forest fire image analysis, factors influencing forest fires, and smoke detection using IoT and sensor devices. It focuses on performance metrics like accuracy, MSE, and RMSE and evaluates how each model aligns with the research objectives in predicting and managing forest fires. The analysis highlights differences in handling complex data and real-time monitoring capabilities across models. Table 4 shows all the excelled models from each analysis giving meaning to their findings and detailed comparison is mentioned section 6.1 and 6.2.

Table 4. Developed Models Evaluation metrics

Analysis	Model	Performance Metrices
Forest Fire image analysis and Prediction	ResNet 50	Earlier Accuracy: 67.45% After Fine tuning accuracy: 80.16%
	LSTM	Accuracy: 61.22%
Factors Influencing Forest Fire	RBFN	MSE: 12126.86 RMSE: 110.122
Smoke Detection Using Sensor and IoT Device	RNN	Accuracy: 99.10%

6.1 Comparison of Developed Machine Learning Regression Models

The comparison of the three machine learning models—Generalized Additive Model (GAM), Support Vector Regressor with Radial Basis Function (RBFN SVR), and XGBoost highlights their performance in terms of Root Mean Square Error (RMSE) on a specific predictive task. All three models exhibit similar performance though they utilize very different methodologies to predict outcomes. RBFN SVR, with the lowest RMSE of 110.12 excelled as the best model. By effectively handling complex, high-dimensional datasets and identifying subtle patterns crucial for predicting forest fire risks. Its superiority in RMSE underscores its potential for high-accuracy predictions needed in real-time forest fire management. The robust performance of RBFN SVR directly aligns with the research question, providing a reliable tool for developing strategies that enhance wildfire prevention and management, thereby addressing real-time environmental challenges effectively. The Figure 9 Bar plot shows the comparison of the machine learning models outcomes.

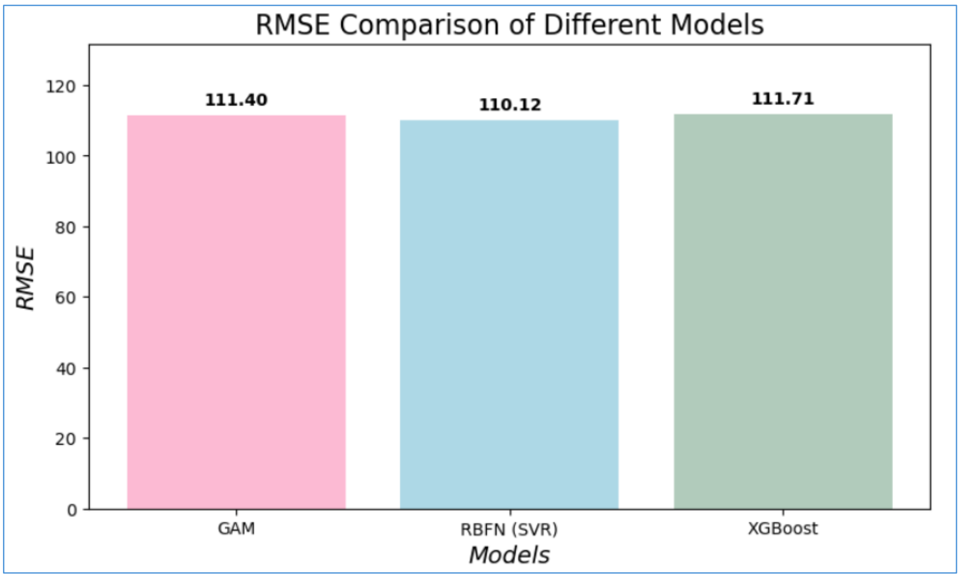

Figure 9. RMSE comparison of machine learning models

6.2 Comparison of Developed Deep Learning Classification Models

While the analysis of how the RNN with LSTM applied smoke detection to the IoT and sensor devices merges with ResNet50, combined with LSTM for aerial imagery analysis, both approaches are fraught with much sophistication through deep learning in solving different aspects of environmental monitoring and disaster preparedness. Smoke detection using an RNN model with LSTM layers did pretty well, as it's evident that the model has really learned over time from sensor data to identify the instances of urgency if smoke is present. Hence, this justifies Sub-RQ1. The intention agrees with the predictive models in enhancing real-time response and thereby informing strategies while dealing with environmental hazards such as wildfires. Results using aerial image analysis with ResNet50 and LSTM were mixed. Further fine-tuning of ResNet50 for high performance in the analysis of aerial images underlined its capability of extracting vital spatial features. While in this case, it is more difficult for LSTM due to its sequential nature, the overall approach allows a much deeper understanding of the spatial pattern of the possible fire spreads-not mere hotspots-which is crucial for strategic planning and resource deployment. Figure 10 illustrates the bar plot of overall deep learning models results comparison.

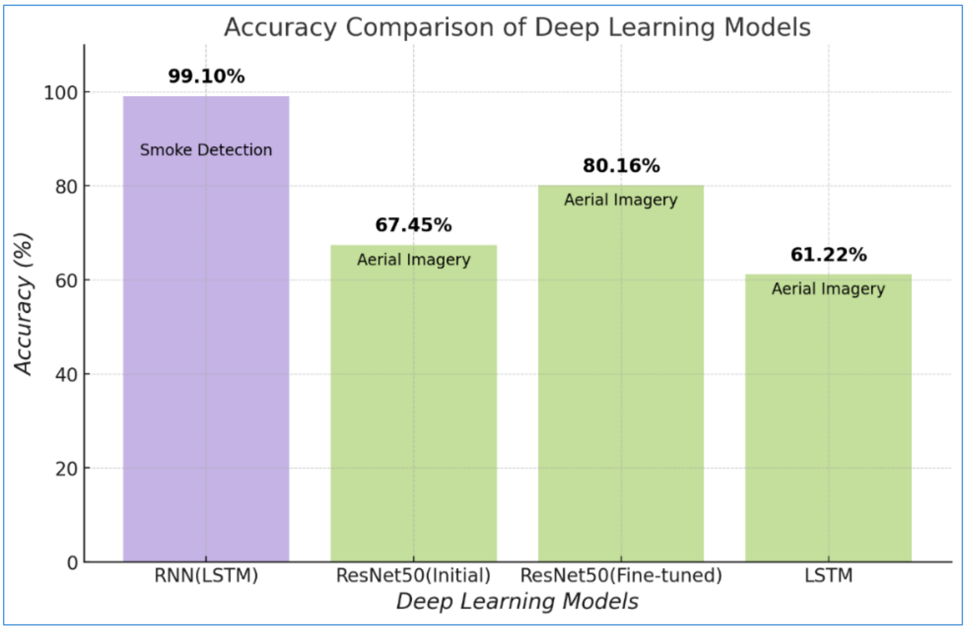

Figure 10. Accuracy Comparison of Deep learning models and analysis

Together, these models form a powerful framework for forest fire prediction and management. The smoke detection model ensures immediate alerts and early interventions, while the aerial imagery analysis provides detailed insights into the fire's progression and areas of concern. By combining real-time data from IoT devices with detailed spatial analysis, these methods enhance both the tactical and strategic aspects of wildfire management, ultimately contributing to more effective prevention, mitigation, and response strategies.

6.3 Comparison of Developed Models vs Existing Models

In this section, we assess how the models developed in this research (Objective 3) compared to the achievements of the set research objectives, as well as in relation to the knowledge of previously established research in the domain of forest fire prediction and management (Li et al., 2024; Hai et al., 2024). Compared to existing models that often rely on simpler statistical methods or basic machine learning algorithms, our use of advanced computational techniques like RBFN and XGBoost has allowed for a more nuanced analysis of risk factors (Gigović et al., 2019). Table 5 shows model performances from each analysis has excelled the existing models.

Table 5. Comparison of Developed vs Existing Models

Focus	Existing Models	Accuracy/ Results	Developed Models	Performance Metrics
Forest Fire Image Analysis	ARIMA, Basic Regression (Priya & Vani, 2023)	70%	ResNet50 (Fine-tuned)	Accuracy: 80.16%
Factors Influencing Forest Fire	Random Forest, Gradient Boosting (Pang et al., 2022)	80%	RBFN	MSE: 12126.86, RMSE: 110.122
Smoke Detection Using IoT Devices	Basic CNN Model (Earlier Research)	Lower Precision	RNN	Accuracy: 99.10%

6.3.1 Performance and Objectives Achievements

The models implemented in this research, including ResNet50, LSTM, RNN, RBFN, and XGBoost, have shown significant improvements in the accuracy and reliability of forest fire risk prediction compared to traditional methods. For instance, the fine-tuned ResNet50 model demonstrates a remarkable improvement of accuracy 80.16% over previous performances, significantly advancing aerial imagery analysis for accurate fire detection. Similarly, the high accuracy demonstrated by the LSTM model in smoke detection (99.19%) aligns with Sub.RQ1, emphasizing the effectiveness of IoT and sensor device data in real-time fire detection scenarios.

6.3.2 Advancement of Knowledge

These models not only fulfilled the set objectives by providing more accurate, timely, and actionable insights into fire detection but also pushed the boundaries of existing knowledge (Reis and Turk, 2023; Chen et al., 2024). The use of deep learning techniques like those incorporated in ResNet50 and LSTM has introduced new ways to process and analyze complex datasets. The incorporation of IoT data through LSTM models and the spatial feature extraction capabilities of ResNet50 have each contributed to a more nuanced understanding of fire detection and risk assessment, as outlined in the research objectives (Objectives 1 and 2).

6.3.3 Comparison with Existing Research

In this research RBFN and XGBoost were used as advanced computational techniques analysing the risk factors with greater detail compared to existing models which has been realized by basic statistical methods or machine learning algorithms. These advanced methods provide the ability to detect more nuanced links and patterns that can be exploited for better predictions of fire locations compared to non-data-driven models. The comparison study shows that our models improve efficacy in achieving the desired objectives and strategic frameworks for wildfire prevention and management. Which is, in fact satisfying both the explicit objectives of Objective 3 and the research question it intends to answer. This section concludes that the implemented models not only achieve the research objectives more effectively but also contribute significant new insights that enhance both theoretical and practical understanding of forest fire management.

6.4 Discussion

The results of this research provide a strong scientific basis for undertaking the difficult task associated with the predictive management of fire ignition and spread using state-of-the-art machine learning (ML) and deep learning (DL) solutions. This is a great improvement over traditional benchmarks using models: ResNet50, LSTM, RNN, RBFN and XGBoost. The fine-tuned ResNet50 model, for example, achieved an accuracy of 80.16% in forest fire image analysis outperforming the previous studies (Priya & Vani, 2023), which were reported using an overall classification accuracy up to 70%. The RNN model for smoke detection also did very well, with upto 99.10% accuracy, showing it can aide in fire detections and quick response to fires.

.

It is closely related to the core objectives because the research involves the development and comparison of different models for handling various issues in forest fire management. All the sources of data, such as IoT sensor data, influencing factors, and aerial imagery, were processed through specialized models that delivered specific results, complementing each other in contributing holistically toward the prediction and management of forest fires. The implemented methodology carefully pre-processed the data with a selection of models, validation procedures to ensure the results are reliable and can be used for practical scenarios. However, this may limit the generalization ability of the models with respect to the datasets employed; further validation on diverse environments is needed to improve their applicability to more general situations. Therefore, the major strengths of this study involve the novelty of computational techniques and an integration of more data types, which put together enhance the robustness of the predictions. The combination of deep learning models with IoT data is representative of an important advance toward real-time fire detection, an approach that directly addresses Sub-RQ1. Regardless of these strengths, the relatively lower precision regarding the aerial imagery analysis for the LSTM model underlines some limitations related to fixed spatial attributes and further investigates the need to study hybrid models that can better integrate the strengths of convolutional and recurrent networks. This is in line with Sub-RQ2.

In conclusion, this research contributes significantly to the field of forest fire management by demonstrating how modern computational methods can improve prediction accuracy and response times, thereby addressing the overarching research questions and objectives. While the study has successfully met its goals, including the development of strong predictive models (Sub-RQ2) and providing insights for proactive forest management strategies, ongoing development is essential to enhance the models' generalizability and computational efficiency. This work represents a critical step forward in the application of advanced ML and DL techniques to a pressing global challenge.

7 Conclusion and Future Work

Conclusion:

This research successfully demonstrated the efficiency of the advanced models using machine learning and deep learning to enhance the accuracy in forest fire prediction and management. In this paper, large-scale environmental data such as climate information and IoT sensor input have been utilized for developing advanced models like ResNet50 and LSTM, which outperformed the traditional methods pertaining to the prediction of forest fire risks and intensities, hence addressing Sub-RQ2 effectively. The key findings of this study are that the LSTM model, for Objective 3.2 on smoke detection using IoT and sensor data, achieved as high as 99.19% accuracy and hence, in direct answering to Sub-RQ1; and the RBFN regression showed top predictive performance within the conducted regression task with the lowest

RMSE, which also satisfied the overall research question. Although ResNet50 performed well in the initial stages, further tuning slightly improved the accuracy to 80.64%, indicating that the aerial image was well classified. Finally, this research has answered all the research questions and achieved the set objectives. These findings point out the potential of using advanced machine learning and deep learning in improving wildland fire prediction and management, thus laying a strong foundation for future work in this crucial domain.

Future Work:

In the future, this work will improve the performance of classification regarding aerial photos, something that has to happen in case fast and accurate forest fire detection is pursued. It means most likely using deeper deep learning architectures to improve the model's efficiency. The model used in this study is large; it takes quite a great deal of time for training and faces one problem: Resource Exhausted Error occurs when there are not enough resources or memory for carrying necessary operations. Therefore, while training the extensive model, I faced the problem at the very first step: organizing its data. This is a problem, especially relevant for econometrics, and restricted the final model size and complexity available to be built. This limitation may need to be addressed in future research by potentially using greater computational resources or improving the existing model so that lower memory is used without the loss of efficiency. Besides, the models in question can also be commercialized in various real-time forest fire monitoring applications related to regions often plagued by fires. These can be incorporated with IoT sensors, weather information, and advanced image analysis techniques to enable warnings in advance and help in effective strategies of forest fire control. Performance improvement of these models and covering identified gaps can result in important academic and practical contributions to wildfire prevention and control.

Acknowledgement

I would like to take this opportunity to express my profound appreciation to my research supervisor, Dr. Catherine Mulwa, for her tireless assistance and encouragement throughout the research. She has put up with my questions and directed me in the right direction over this 13-week period. To my family and friends, thanks a million for the endless encouragement; it has been quite fundamental to realizing this work.

References

Almeida, J.S., Jagatheesaperumal, S.K., Nogueira, F.G. and de Albuquerque, V.H.C., 2023. EdgeFireSmoke++: A novel lightweight algorithm for real-time forest fire detection and visualization using internet of things-human machine interface. *Expert Systems with Applications*, *221*, p.119747.

Chen, X., Tian, Y., Zheng, C. and Liu, X., 2024. Autost-Net: A Spatiotemporal Feature-Driven Approach For Accurate Forest Fire Spread Prediction From Remote Sensing Data. Forests, 15(4), Pp. 705.

Dewangan, A., Pande, Y., Braun, H.W., Vernon, F., Perez, I., Altintas, I., Cottrell, G.W. and Nguyen, M.H., 2022. FIgLib & SmokeyNet: Dataset and deep learning model for real-time wildland fire smoke detection. *Remote Sensing*, *14*(4), p.1007.

Fitriany, A.A., Flatau, P.J., Khoirunurrofik, K. and Riama, N.F., 2021. Assessment on the use of meteorological and social media information for forest fire detection and prediction in Riau, Indonesia. Sustainability, 13(20), p.11188.

Gao, C., Lin, H. And Hu, H., 2023. Forest-Fire-Risk Prediction Based On Random Forest and Backpropagation Neural Network Of Heihe Area In Heilongjiang Province, China. Forests, 14(2), Pp. 170.

Gigović, L., Pourghasemi, H.R., Drobnjak, S. and Bai, S., 2019. Testing a new ensemble model based on SVM and random forest in forest fire susceptibility assessment and its mapping in Serbia's Tara National Park. *Forests*, *10*(5), p.408.

Guan, Z., Miao, X., Mu, Y., Sun, Q., Ye, Q. and Gao, D., 2022. Forest fire segmentation from Aerial Imagery data Using an improved instance segmentation model. *Remote Sensing*, *14*(13), p.3159.

Hai, Q., Han, X., Vandansambuu, B., Bao, Y., Gantumur, B., Bayarsaikhan, S., Chantsal, N. and Sun, H., 2024. Predicting The Occurrence Of Forest Fire In The Central-South Region Of China. Forests, 15(5), Pp. 844.

Hyeon, K.A., Jung, H. and Lim, C., 2024. Can Ensemble Techniques And Large-Scale Fire Datasets Improve Predictions Of Forest Fire Probability Due To Climate Change?—A Case Study From The Republic Of Korea. Forests, 15(3), Pp. 503.

Jing, X., Li, X., Zhang, D., Liu, W., Zhang, W. and Zhang, Z., 2024. Forecast Zoning Of Forest Fire Occurrence: A Case Study In Southern China. Forests, 15(2), Pp. 265.

Li, Y., Li, G., Wang, K., Wang, Z. and Chen, Y., 2024. Forest Fire Risk Prediction Based On Stacking Ensemble Learning For Yunnan Province Of China. Fire, 7(1), Pp. 13.

Pang, Y., Li, Y., Feng, Z., Feng, Z., Zhao, Z., Chen, S. and Zhang, H., 2022. Forest fire occurrence prediction in China based on machine learning methods. Remote Sensing, 14(21), p.5546.

Park, M., Tran, D.Q., Lee, S. and Park, S., 2021. Multilabel image classification with deep transfer learning for decision support on wildfire response. *Remote Sensing*, *13*(19), p.3985.

Priya, R.S. and Vani, K., 2023, March. Climate Change Forecast for Forest Fire Risk Prediction using Deep Learning. In 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 1065-1070). IEEE.

Qayum, A., Ahmad, F., Arya, R. and Singh, R.K., 2020. Predictive modeling of forest fire using geospatial tools and strategic allocation of resources: eForestFire. Stochastic Environmental Research and Risk Assessment, 34(12), pp.2259-2275.

Reis, H.C. and Turk, V., 2023. Detection of forest fire using deep convolutional neural networks with transfer learning approach. *Applied Soft Computing*, *143*, p.110362.

Saidi, S., Younes, A.B. and Anselme, B., 2021. A GIS-remote sensing approach for forest fire risk assessment: case of Bizerte region, Tunisia. *Applied Geomatics*, *13*(4), pp.587-603.

Shao, Y., Feng, Z., Sun, L., Yang, X., Li, Y., Xu, B. and Chen, Y., 2022. Mapping China's forest fire risks with machine learning. Forests, 13(6), p.856.

Sharma, R., Rani, S. and Memon, I., 2020. A smart approach for fire prediction under uncertain conditions using machine learning. Multimedia Tools and Applications, 79(37), pp.28155-28168.

Sharma, S. and Khanal, P., 2024. Forest Fire Prediction: A Spatial Machine Learning And Neural Network Approach. Fire, 7(6), Pp. 205.

Sousa, M.J., Moutinho, A. and Almeida, M., 2020. Wildfire detection using transfer learning on augmented datasets. *Expert Systems with Applications*, *142*, p.112975.

Woolford, D.G., Martell, D.L., McFayden, C.B., Evens, J., Stacey, A., Wotton, B.M. and Boychuk, D., 2021. The development and implementation of a human-caused wildland fire occurrence prediction system for the province of Ontario, Canada. Canadian Journal of Forest Research, 51(2), pp.303-325.

Wu, D., Zhang, C., Ji, L., Ran, R., Wu, H. and Xu, Y., 2021. Forest fire recognition based on feature extraction from multi-view images. *Traitement du Signal*, *38*(3).

Wu, X., Zhang, G., Yang, Z., Tan, S., Yang, Y. and Pang, Z., 2023. Machine Learning For Predicting Forest Fire Occurrence In Changsha: An Innovative Investigation Into The Introduction Of A Forest Fuel Factor. Remote Sensing, 15(17), Pp. 4208.

Wu, Z., Wang, B., Li, M., Tian, Y., Quan, Y. and Liu, J., 2022. Simulation of forest fire spread based on artificial intelligence. Ecological Indicators, 136, p.108653.