Deep Learning Models for Forest Fire Detection: A Comparative Image Classification Study

Dissertation submitted to School of Business for the partial fulfilment of the degree of

Bachelor of Business Administration (Analytics and Big Data)

UNDER THE GUIDANCE OF:
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(May, 2024)

STUDENT DECLARATION

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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I extend my heartfelt thanks to all individuals who have been part of this enriching journey and have contributed to the successful completion of my dissertation report.

UNIVERSITY MENTOR’S CERTIFICATE

This is to certify that the dissertation entitled **"Deep Learning Models for Forest Fire Detection: A Comparative Image Classification Study"** submitted by Vaishali to UPES for partial fulfillment of the requirements for BBA (Analytics & Big Data) is a Bonafede record of the research work conducted under my supervision and guidance. The content of the dissertation, whether in full or parts, has not been submitted to any other institute or university for the award of any other degree or diploma.

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ABSTRACT

Forest fires are a significant concern, causing extensive damage to ecosystems, property, and livelihoods. This study addresses the critical need for enhanced forest fire detection systems by conducting a comparative analysis of deep learning models across G7 countries. This study fills a gap by evaluating the performance and versatility of two popular deep learning approaches: Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. Utilizing a carefully curated dataset of fire and non-fire images, we train and evaluate both models with a 75%-25% split for training and testing data. Our findings indicate that the CNN model outperforms the LSTM model, achieving an accuracy of 87.98% compared to 82.56%. This underscores CNN's effectiveness in detecting forest fires. Our research provides valuable insights, laying the groundwork for the development of more robust and accurate forest fire warning systems across the G7 nations and beyond.

EXECUTIVE SUMMARY

Problem Addressed:

The absence of a comparative assessment of deep learning models for detecting forest fires across G7 nations poses a fundamental challenge in creating efficient detection systems. Current research predominantly revolves around image classification algorithms, overlooking the intricate requirements of forest fire detection. This gap underscores the critical necessity for a comprehensive evaluation to ascertain the effectiveness and suitability of deep learning algorithms in this context.

Objective:

RO1 - To conduct a targeted comparative analysis of two deep learning models for detecting forest fires in G7 nations.

RO2 - To assess the effectiveness and constraints of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks in tasks related to forest fire detection.

Outcome Obtained:

After thorough experimentation and evaluation on a meticulously curated collection of fire and non-fire images, the study discovered that the CNN model beats the LSTM model in detecting forest fires, with an accuracy of 87.98% against 82.56%. This outcome demonstrates CNN's usefulness in addressing forest fire detection issues. The study contributes major insights to the sector, establishing the framework for the creation of more resilient and precise forest fire warning systems in G7 countries and elsewhere.

CHAPTER-1
INTRODUCTION

The forest ecosystem is a highly complex environment covering about 31% of the Earth's land. It plays a crucial role in fighting climate change, achieving carbon neutrality goals, protecting biodiversity, enhancing ecosystem services, and promoting resilient and sustainable economies (FAO, 2022). Forests play a critical role in supporting human well-being and the health of the planet (Razafindratsima et al., 2021). They serve as essential "lungs" for the Earth by absorbing carbon dioxide and producing oxygen, which is essential for all living organisms. Additionally, forests contribute to biodiversity by providing habitats for a wide variety of plant and animal species. They also help regulate the climate by capturing and storing carbon, reducing the effects of global warming. Moreover, forests are crucial for maintaining the water cycle, controlling temperatures, and preventing soil erosion through their root systems. Moreover, forests provide opportunities for recreational activities, elevate the aesthetics of natural environments, and promote mental well-being. They serve as natural filters, eliminating harmful pollutants from both the air and water. Numerous plant species inhabiting forests possess medicinal attributes utilized in traditional medicinal practices. The interconnection among ecosystems, human communities, and the general welfare of the planet underscores the significance of conserving forests and ensuring their sustainable management to uphold a balanced relationship between environmental conservation and human needs (Melaku & Pastor Ivars, 2024).

The continuous decline in tree populations and the overall health of forests is worsened by forest fires, which pose a threat to ecosystems. (Hartmann et al., 2022). Human activities are a significant contributing factor in this situation. Forest fires can start and spread due to a variety of reasons such as discarded cigarettes, unattended campfires, and intentional burning for agricultural purposes. Regions with dense tree coverage are especially vulnerable to human carelessness and deliberate actions, which increase the frequency and intensity of these disasters. Climate variations like rising temperatures and changes in precipitation patterns also play a role in the rapid spread of wildfires. Extended periods of dry weather as a result of climate change further increase the danger and severity of forest fires.

Invasive species play a role in decreasing the number of trees in forested areas by changing the structure of the forest and making it easier for fires to spread (Attri et al., 2020). These invasive plants make it more likely for native plants to be harmed by fire. Diseases and pests also contribute to tree health problems. Trees that are already sick or infested are more likely to be damaged by fires. Bark beetles, for example, can kill trees, leaving behind dry wood that can fuel fires and make the damage worse.

Ineffective fire management practices result in the buildup of combustible materials in forests. In the absence of controlled burning or measures to mitigate fuel accumulation, the proliferation of fuels heightens the risk of more intense fires, resulting in substantial damage to tree populations.

Urbanization and habitat fragmentation pose serious challenges, especially when cities expand into forested areas. This increases the risk of accidental fires as human activity comes closer to natural surroundings. The changing landscape disrupts the natural fire patterns in forests, causing imbalances in ecosystems and a decrease in tree numbers. Public awareness is key in raising understanding of the dangers of forest fires and rallying efforts to prevent and reduce the risks associated with these destructive disasters.

Forest fire in the context of India

According to the India State of Forest Report (ISFR), Forest fires are a regular phenomenon in our country often observed during summers. A number of **52,785 forest fires were detected using MODIS** (Moderate Resolution Imaging Spectro-radiometer) sensor and **3,45,989 forest fires were detected using SNPP-VIIRS** (Suomi-National Polar-orbiting Partnership - Visible Infrared Imaging Radiometer Suite) in forest fire season from Nov 2020 to June 2021. Every year large areas of forests are affected by fires of varying intensity and extent. Based on the forest inventory records, **54.40% of forests in India are exposed to occasional fires, 7.49% to moderately frequent fires, and 2.40% to high incidence levels while 35.71% of India's forests** have not yet been exposed to fires of any real-significance. (*FSI*.(n.d.),2024)

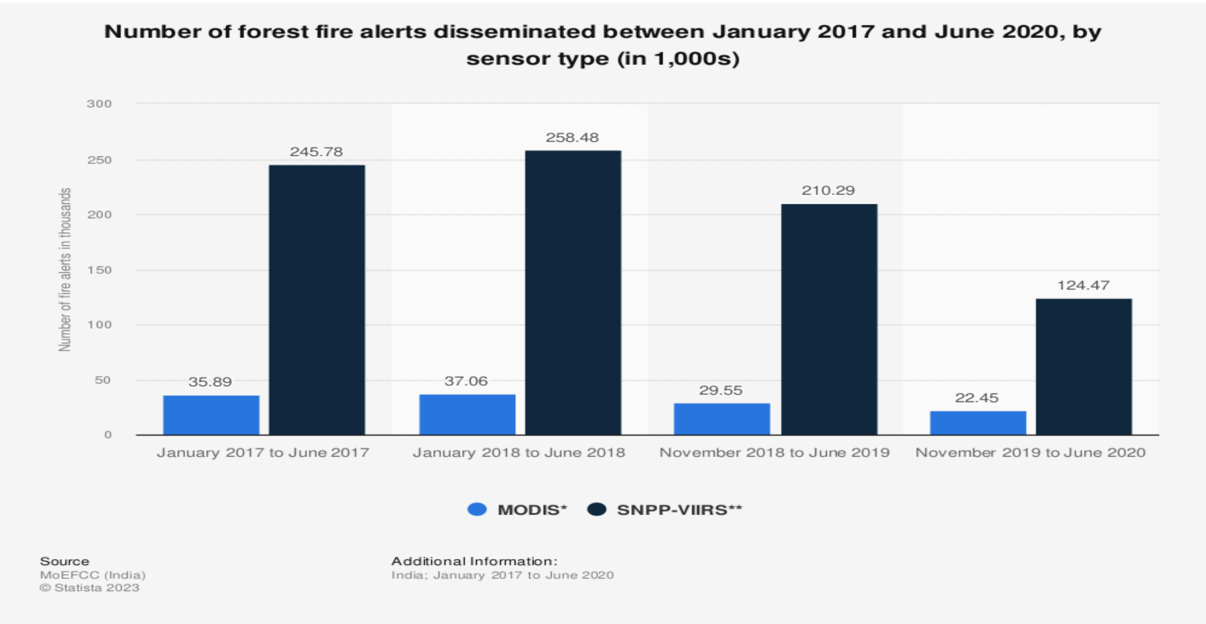

Figure 1: (Source: Statista, 2021)

According to the India State of Forest Report (ISFR) for 2021, India's forest and tree cover totals **7,13,789** square kilometres, or **21.71%** of its total geographic area. Forest types range from subtropical dry deciduous to tropical wet evergreen, with the Himalayas containing **10%** temperate and alpine woods. India has over **425** plant species, and forestry is the second most important terrestrial sector, accounting for **21.34%** of the country's surface. However, deforestation due to logging, grazing, and agricultural expansion has resulted in significant forest loss. The **Chipko movement** of **1973** emphasized the need of forest preservation and gender equality in environmental advocacy, resulting in the formation of feminist environmental organizations.

In the context of Worldwide

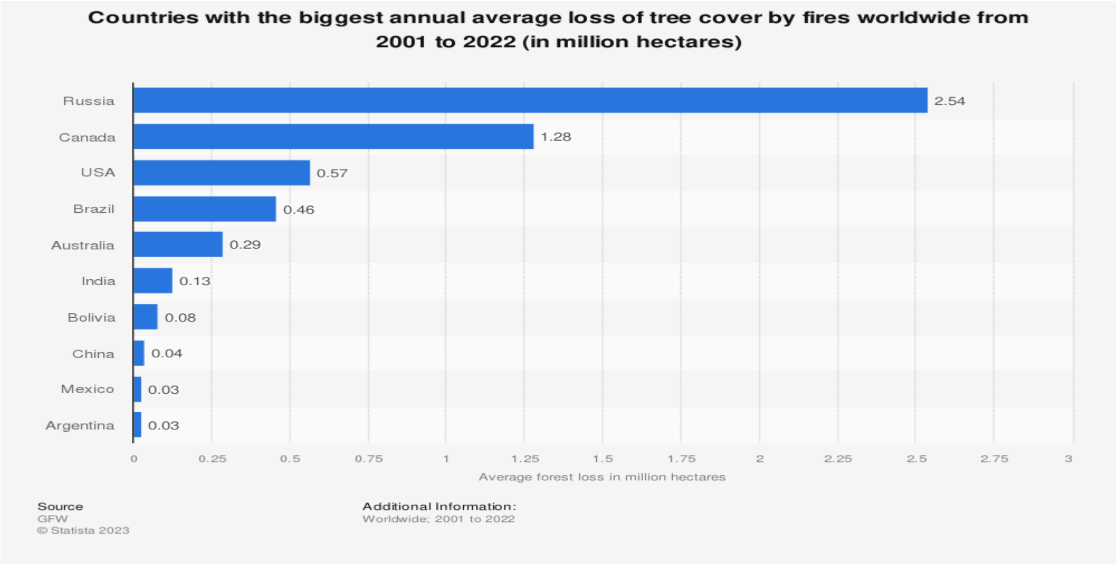

Figure 2: (Source: Statista, 2023)

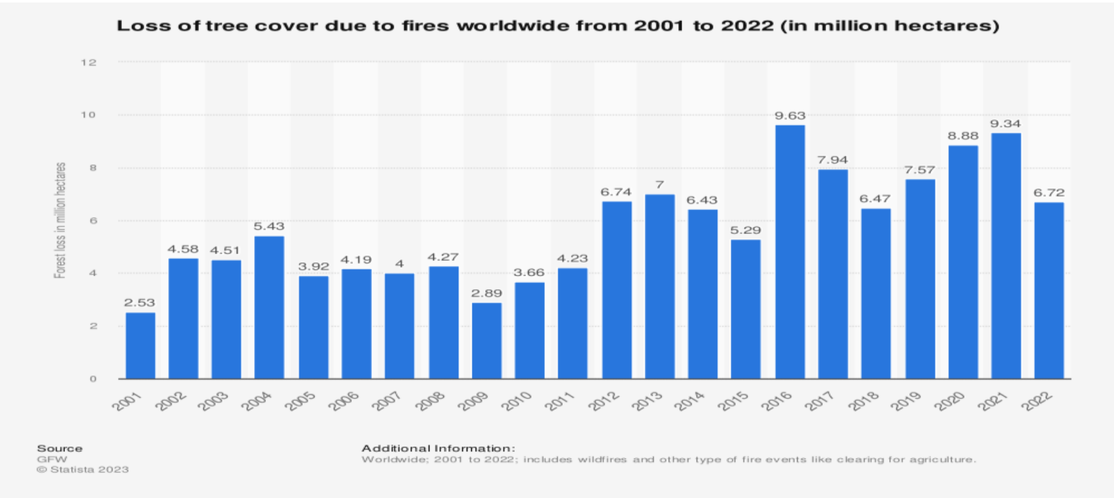

Figure 3: (Source: Statista, 2023)

Fires are impacted by specific environmental factors determined by the interaction of weather, fuel, and geography, forming what is known as the fire behaviour triangle. Essentially, weather elements like temperature and wind play a significant role. High temperatures and strong, hot winds contribute to a heightened fire risk. Fuel, consisting of materials such as fallen leaves, wood, grass, and shrubs on the forest floor, is another critical component. Without these flammable components, forest fires would not occur. Additionally, terrain features such as altitude, slope, and aspect are important. These characteristics influence temperature and precipitation patterns, thereby shaping conditions conducive to fires. This study explores how these three elements intersect to create an environment favourable for forest fires, with the aim of providing insights for enhancing fire management and prevention strategies.

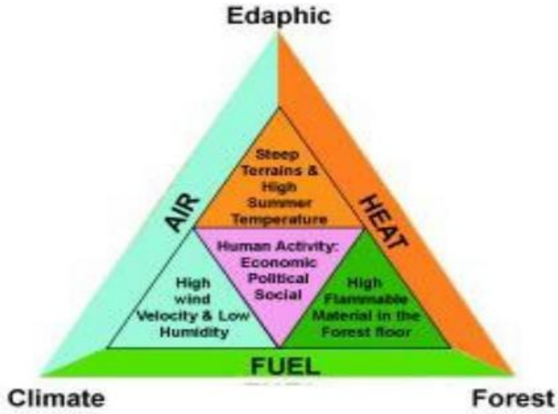

Figure 4: Fire environment triangle (Source: Roy, 2003)

Classification of Forest Fires

Forest fires are categorized based on both their causes and locations. Regarding causative factors, they can be classified as natural fires, occurring without human involvement and often ignited by factors like lightning; accidental fires, unintentionally caused by human activities such as unattended campfires or discarded cigarettes; and deliberate fires, purposefully started, perhaps for activities like land clearing or, unfortunately, through arson.

Causes of Forest Fire

Forest fires happen because of either nature or people. Surprisingly, more than 95% of these fires are caused by humans. When it comes to natural fires, they usually start with things like lightning or when stones roll and dry bamboos rub together in the wind. Now, human-made fires can be on purpose or by accident. On purpose, people might start fires to make more grass grow for animals to eat, to scare away animals damaging their crops, or to collect things like honey and flowers that fall on the ground. Accidental fires, on the other hand, can happen when someone is careless with matches, cigarettes, or fires in general. They can also start at campsites, picnics, or even from sparks from trains.

Researching forest fires is super important to figure out where they come from and why we need to keep studying them. These fires are like big, uncontrollable events that mess up the whole natural system. The main goal of this research is to find ways to protect forests from these fires. Our human activities are causing a lot of problems for the environment, and it's affecting the variety of living things, like plants and animals. This is where forests come in because they are crucial for keeping different types of life. Unfortunately, fires and other things are harming these forests, which is a big worry.

Climate change is one of the major drivers of increasing fire activity. Extreme heat waves are already five times more likely today than they were 150 years ago and are expected to become even more frequent as the planet continues to warm.

PROBLEM STATEMENT

The absence of a comparative analysis on deep learning models for forest fire detection in G7 nations hinders the development of effective detection strategies. Current research predominantly focuses on image classification methods, overlooking the nuanced requirements of forest fire detection. There is an urgent need for a comprehensive study to evaluate the performance and suitability of deep learning approaches in this context.

SCOPE OF THE STUDY

This study will encompass a comparative analysis of deep learning models, specifically CNN and LSTM, for forest fire detection in G7 nations. It will evaluate the models' performance in terms of accuracy, efficiency, and adaptability across diverse geographic and environmental conditions within G7 countries. The scope also includes identifying potential areas for improvement in existing detection strategies and informing the development of more effective forest fire detection systems tailored to the unique challenges of G7 nations.

MOTIVATION

The devastating impact of forest fires on ecosystems, economies, and communities underscores the critical need for effective detection and mitigation strategies. By conducting a comparative analysis of deep learning models for forest fire detection in G7 nations, this study aims to address the gap in research and contribute to the development of more robust and efficient detection systems. By enhancing our understanding of the performance and limitations of existing models, the study seeks to empower policymakers, researchers, and stakeholders with valuable insights to better protect vulnerable regions and minimize the impact of forest fires.

CHAPTER-2
LITERATURE REVIEW

Yuwen Peng et al. (2024) have developed a model for reconstructing historical forest fire danger in Sichuan Province, China. The study employed a deep learning-based time series model and spatial interpolation approaches. By evaluating three different models (ARIMA, Prophet, and LSTM), they found that out of the three, LSTM is one of the best models for predicting the modified forest fire danger index (MFFDI). This indicates that the LSTM model is more reliable in capturing past MFFDI values and can rebuild forest fire risk. The researchers validate their findings by comparing them with real forest fire events.

Xufeng Lin et al. (2023) the researcher has proposed a comprehensive study of forest fire prediction, highlighting its importance globally to overcome its effects. The study has explored various methods of predicting forest fires including machine learning, remote sensing, and GIS techniques. This study highlighted the effectiveness of the deep learning models especially the long and short-term time series network (LSTNet), in enhancing the accuracy. They did a comparative study by comparing the performance of LSTNet model machine learning methods using metrics like Root mean squared error (RMSE) and ACC. The paper also addressed the issue of unbalanced classification within forest fire datasets by employing an oversampling method. The findings of the study highlight the ongoing advancement in forest fire predictions, offering valuable insights for wildfire management at the global scale.

Abolfazl Abdollahi et al. (2023) The research aims to develop a method and create a way to predict when wildfires may occur in the region of Victoria, Australia. Based on weather conditions, landscape, and vegetation types, the study aims to determine the likelihood of wildfires. The SHAP method is used in this study to assess the importance of different factors and explain how the model works. This model allows for a thorough study, helping to choose the best models for accurately predicting the wildfires in that region.

Hatice Catal Reis et al. (2023) the study explore that forest fires are a threat to the environment and it is very important to detect them to protect the environment and respond effectively. They employed the M-2 algorithm for forest fire detection. Which results in accurate prediction rates with fewer misclassifications. Model parameters were adjusted
using different techniques that target some parameters such as kernel type, gamma, and cross-validation. the performance of the model was evaluated with the use of metrics such as accuracy, precision, recall, and F1 score.

Yaowen Hu et al. (2022) The research introduces a new technique known as MVMNet for identifying smoke in forest fires from different viewpoints, with impressive accuracy and effectiveness. This method utilizes a conversion-attention mechanism, Softpool-spatial pyramid pooling, and hybrid nonmaximum suppression approaches to improve detection accuracy. MVMNet effectively addresses issues like smoke seen from varying perspectives, possible confusion with other objects, and faraway smoke captured by the camera. Furthermore, the authors offer access to the datasets used in the research and code for format conversion upon request.

Nosheen Abid et al. (2021) have developed a deep-learning system to identify burnt areas by analysing satellite images. The study employed advanced feature extraction techniques and clustering algorithms to create training labels. the model had an F1 score of 0.87 which indicates the model is effective in identifying the burnt areas. The study highlights the significance of the deep learning approach of mapping the burned areas as compared to other traditional methods.

Medi Rahul et al. (2020) The research focuses on using a Convolutional Neural Network (CNN) to detect forest fires early by fine-tuning the ResNet50 architecture. Transfer learning with models like VGG16, ResNet50, and DenseNet121 is used to improve training and test accuracy, with a special emphasis on the effectiveness of ResNet50. The research also looks at traditional methods for forest fire detection, such as wireless sensor networks, YOLOv3, Faster R-CNN, and smoke detection algorithms. An original approach combines motion and colour detection to speed up fire detection and enhance accuracy, even in the face of certain limitations.

R. Shanmuga Priya et al. (2019) The research focuses on using satellite images for forest fire detection. Employing convolutional neural network (CNN) based Inception -V3 model with transfer learning. and the model is more effective and accurate than other existing models. The dataset includes satellite images collected from NASA and Google. 481 images for the training set and 53 images for the testing set. The model accuracy scores 98% for detecting forest fires.

George et al. have explored the risk of forest fires through forecasting algorithms based on datasets. In a separate study, Mauro Castelli, Leonardo Vanneschi, and Ales Popovic investigated the analysis of burned areas and introduced an innovative approach called Genetic Programming (GP). Their primary objective was to develop a system capable of predicting the extent of land affected by forest fires. Their research revealed that Geometric Semantic Genetic Programming (GSGP) outperforms other methods, thanks to its ability to generate succinct conclusions effectively.

Paulo et al. employed a data mining method to forecast the magnitude of forest fires. Their research revealed that integrating four meteorological variables through an optimized Support Vector Machine (SVM) configuration proved successful in predicting smaller burned areas. This insight holds significant importance for the allocation of firefighting resources.

RESEARCH GAP

Despite advancements in image classification techniques, there's a lack of comparative analysis specifically focused on deep learning models for forest fire detection in G7 nations. Existing studies predominantly explore image classification methods, highlighting the need for a comprehensive evaluation of deep learning approaches in this context to discern their effectiveness and limitations.

RESEARCH OBJECTIVE

RO1 - To conduct a targeted comparative analysis of two deep learning models for detecting forest fires in G7 nations.
RO2 - To assess the effectiveness and constraints of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks in tasks related to forest fire detection.

CHAPTER-3
METHODOLOGY

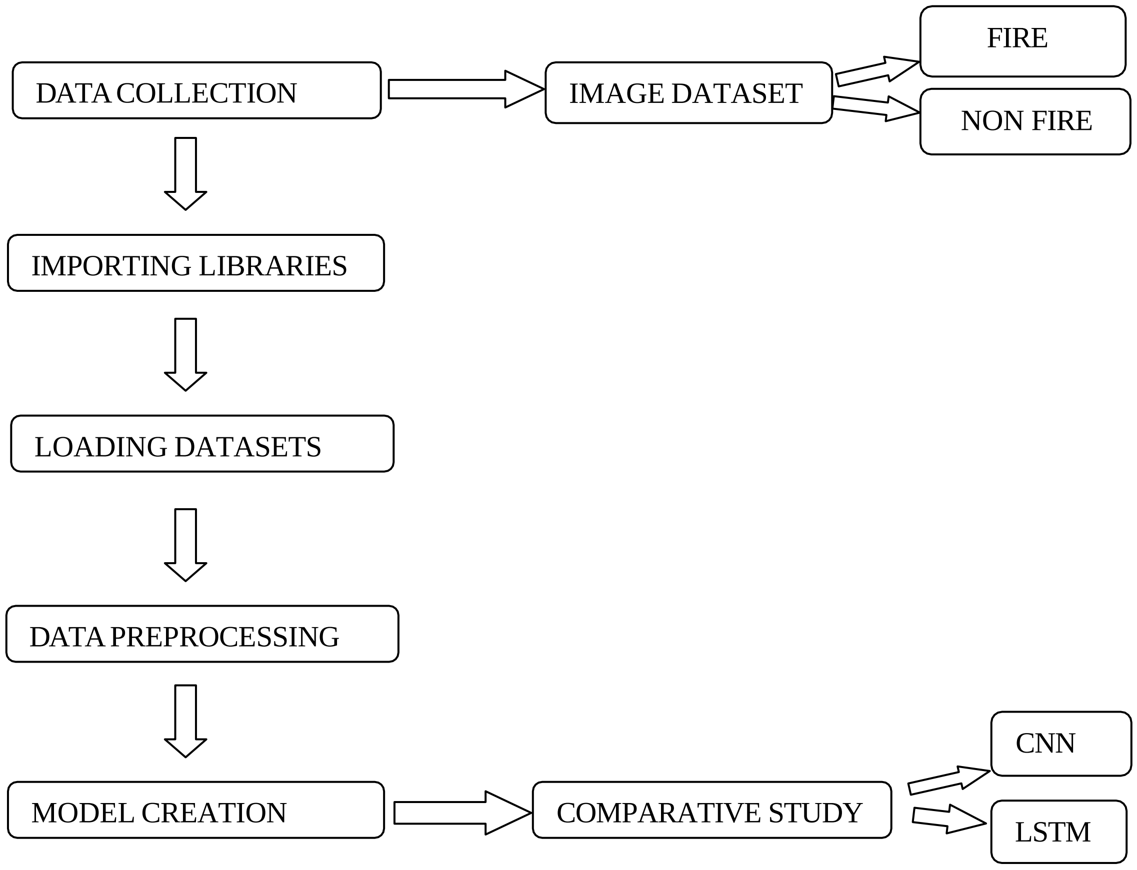

Figure 5: Flowchart of the Study

Dataset

The dataset, named image dataset comprises two classes: 'Fire' and 'Non_Fire'. The 'Fire' class have 1442 images while 'Non_Fire' have 2716 images.

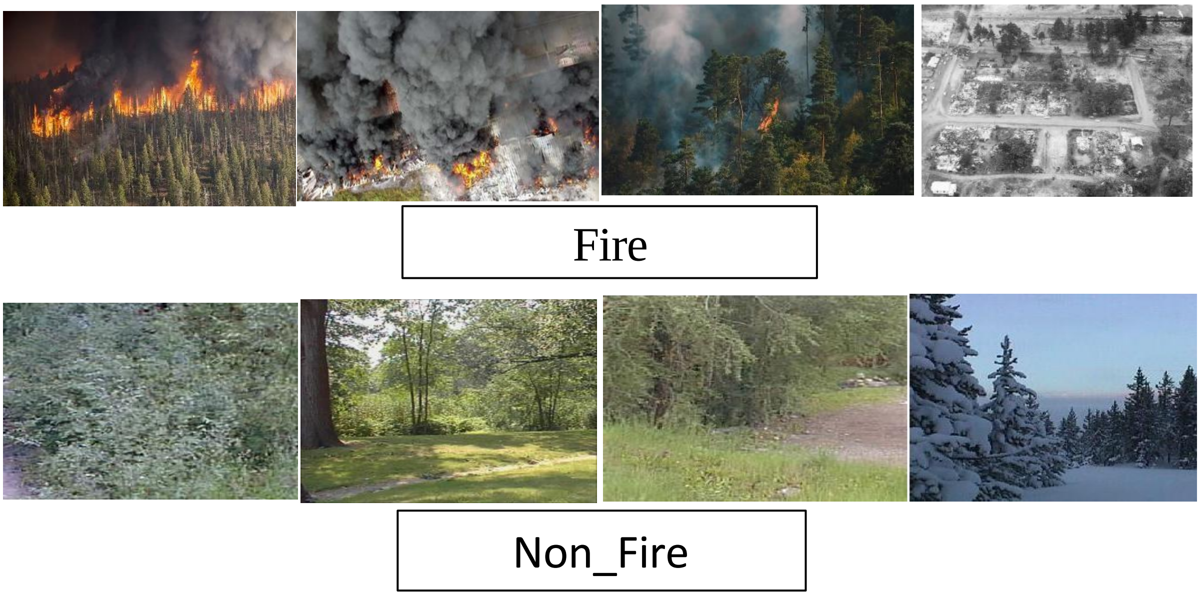

Figure 6. Sample Data

Introduction to CNN Model:

The Convolutional Neural Network (CNN) is a powerful architecture extensively used for image classification tasks like forest fire detection. With its hierarchical structure, consisting of Convolutional, Pooling, Fully Connected, and Dropout layers, CNNs excel at automatically learning and extracting features from images. By employing techniques like data augmentation and batch normalization, CNN models can effectively generalize to new data and mitigate overfitting issues, making them highly suitable for image-based tasks.

Introduction to LSTM Model:

The Long Short-Term Memory (LSTM) model is a specialized variant of recurrent neural networks (RNNs), ideal for capturing long-range dependencies in sequential data. In the provided code snippet, the LSTM model is implemented using TensorFlow's Sequential API, comprising multiple LSTM layers with dropout regularization. Unlike traditional RNNs, LSTM units are equipped with memory cells and gating mechanisms, enabling them to retain and update information over time, overcoming the vanishing gradient problem. This unique architecture enables LSTM models to effectively capture temporal patterns in sequential data, making them well-suited for tasks like natural language processing and time series forecasting, including forest fire detection.

```
model = Sequential()

# CONV => RELU => POOL
model.add(SeparableConv2D(16,(7,7),padding='same',input_shape=(128,128,3)))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))

# CONV => RELU => POOL
model.add(SeparableConv2D(32,(3,3),padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))

# CONV => RELU => CONV => RELU => POOL
model.add(SeparableConv2D(64,(3,3),padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(SeparableConv2D(64,(3,3),padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))

# first set of FC => RELU layers
model.add(Flatten())
model.add(Dense(128))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
```

```
# softmax classifier
model.add(Dense(len(classes)))
model.add(Activation("softmax"))

# Remove the 'decay' argument
opt = SGD(learning_rate=INIT_LR, momentum=0.9)


model.compile(loss='binary_crossentropy',
              optimizer=opt,
              metrics=['accuracy'])

print(model.summary())
```

Figure 7: Codes for CNN Model

The process begins with collecting data on forest fires from multiple sources, resulting in an image dataset divided into "fire" and "non-fire" classes. The dataset is then split into two sets: training (75%), and testing (25%). Initial data processing consists of standardizing image size to 128x128 pixels and normalizing pixel values between 0 and 1. TensorFlow is used to generate deep learning models such as CNN and LSTM. The CNN architecture consists of sequential layers that include Convolutional, Pooling, and Fully Connected layers, as well as activation functions and batch normalization to improve model performance. Augmentation techniques like as rotation, zoom, and shift are used to expand the training dataset and improve model resilience.

Model training employs the stochastic gradient descent (SGD) optimizer with a learning rate of 0.1 and momentum of 0.9, as well as the computation of class weights to correct imbalances. The binary cross-entropy loss and accuracy measures are used to evaluate models. Training lasts 50 epochs and has a batch size of 64, with continuous performance evaluation on both the training and validation datasets. Finally, the model is evaluated on the testing dataset, and predictions are shown to assess its performance in forest fire detection.

```
# Create LSTM model
model = Sequential()
model.add(LSTM(128, input_shape=(128, 128*3), return_sequences=True))
model.add(Dropout(0.5))
model.add(LSTM(128, return_sequences=False))
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu'))
model.add(BatchNormalization())
model.add(Dense(1, activation='sigmoid'))  # Changed to 1 unit and sigmoid activation
# Compile model
opt = Adam(learning_rate=INIT_LR)
model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy'])

# Display model summary
print(model.summary())
```

Figure 8: Codes for LSTM Model

The process begins with data collection and preprocessing, where images of forest fires and non-fire scenarios are resized, normalized, and split into training and testing sets. Input data is reshaped to fit the LSTM model's sequential processing requirement. The model architecture comprises two LSTM layers followed by dropout layers for regularization and a fully connected layer for feature extraction. Batch normalization is applied to stabilize training, and the final layer performs binary classification using sigmoid activation. Training utilizes the Adam optimizer with binary cross-entropy loss, iterating over 50 epochs with a batch size of 32. Validation data is employed to monitor model performance, and the trained model is saved for future use. Training history is visualized to assess loss and accuracy metrics, providing insights into model performance throughout the training process.

CHAPTER-4
RESULTS

As a result of the study, it was found that the CNN model exhibited superior accuracy, achieving 0.8798 compared to LSTM's 0.8256 in forest fire image classification. This highlights CNN's effectiveness in accurately identifying forest fire patterns, crucial for timely detection within the G7 nations. While LSTM also performed well, its slightly lower accuracy suggests potential limitations in capturing temporal dependencies within image sequences. These findings underscore the importance of leveraging CNNs' ability to extract spatial features for image classification tasks, particularly in forest fire detection contexts. The study's outcomes have significant implications for policymakers and stakeholders involved in optimizing detection strategies, emphasizing the importance of utilizing deep learning techniques, specifically CNNs, to enhance the accuracy and efficiency of forest fire detection systems in G7 countries. Ultimately, this can aid in mitigating the destructive impact of forest fires on ecosystems and communities.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 separable_conv2d (Separabl  (None, 128, 128, 16)      211
 eConv2D)

 activation (Activation)     (None, 128, 128, 16)      0

 batch_normalization (Batch  (None, 128, 128, 16)      64
 Normalization)

 max_pooling2d (MaxPooling2  (None, 64, 64, 16)        0
 D)

 separable_conv2d_1 (Separa  (None, 64, 64, 32)        688
 bleConv2D)

 activation_1 (Activation)   (None, 64, 64, 32)        0

 batch_normalization_1 (Bat  (None, 64, 64, 32)        128
 chNormalization)

 max_pooling2d_1 (MaxPoolin  (None, 32, 32, 32)        0
 g2D)

 separable_conv2d_2 (Separa  (None, 32, 32, 64)        2400
 bleConv2D)

 activation_2 (Activation)   (None, 32, 32, 64)        0

 batch_normalization_2 (Bat  (None, 32, 32, 64)        256
 chNormalization)

 separable_conv2d_3 (Separa  (None, 32, 32, 64)        4736
 bleConv2D)
```

```
 activation_3 (Activation)   (None, 32, 32, 64)        0

 batch_normalization_3 (Bat  (None, 32, 32, 64)        256
 chNormalization)

 max_pooling2d_2 (MaxPoolin  (None, 16, 16, 64)        0
 g2D)

 flatten (Flatten)           (None, 16384)             0

 dense (Dense)               (None, 128)               2097280

 activation_4 (Activation)   (None, 128)               0

 batch_normalization_4 (Bat  (None, 128)               512
 chNormalization)

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 128)               16512

 activation_5 (Activation)   (None, 128)               0

 batch_normalization_5 (Bat  (None, 128)               512
 chNormalization)

 dropout_1 (Dropout)         (None, 128)               0

 dense_2 (Dense)             (None, 2)                 258

 activation_6 (Activation)   (None, 2)                 0

=================================================================
Total params: 2123813 (8.10 MB)
Trainable params: 2122949 (8.10 MB)
Non-trainable params: 864 (3.38 KB)
```

Figure 9: Output of CNN Mode

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_6 (LSTM)               (None, 128, 128)          262656

 dropout_5 (Dropout)         (None, 128, 128)          0

 lstm_7 (LSTM)               (None, 128)               131584

 dropout_6 (Dropout)         (None, 128)               0

 dense_5 (Dense)             (None, 64)                8256

 batch_normalization_2 (Bat  (None, 64)                256
 chNormalization)

 dense_6 (Dense)             (None, 1)                 65

=================================================================
Total params: 402817 (1.54 MB)
Trainable params: 402689 (1.54 MB)
Non-trainable params: 128 (512.00 Byte)
_________________________________________________________________
None
```

Figure 10: Output of LSTM Model

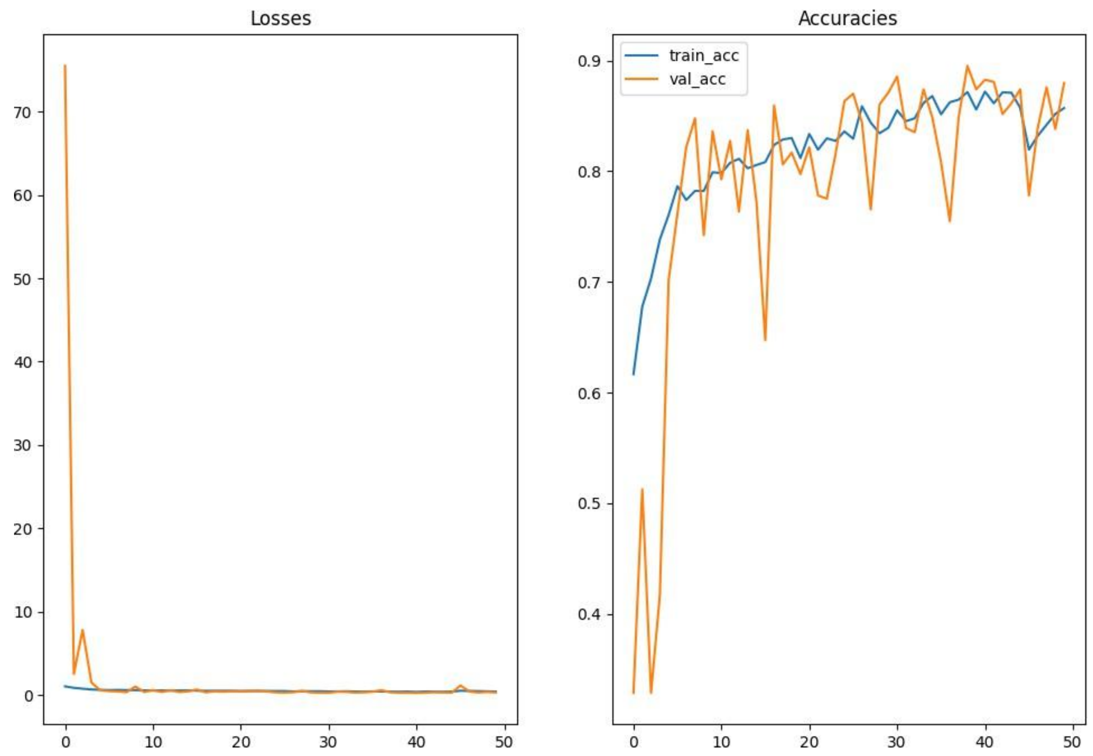

Figure 11: Graphical Representation of Loss & Accuracy (CNN)

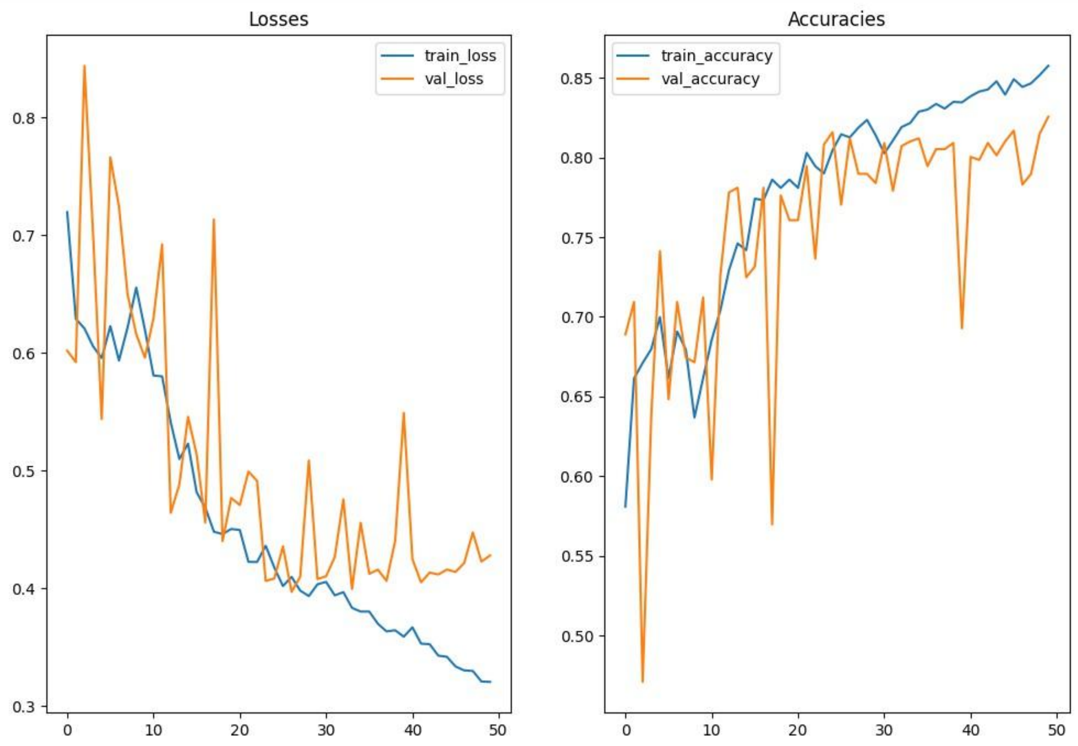

Figure 12: Graphical Representation of Loss & Accuracy (LSTM)

CHAPTER-5
CONCLUSION

This study addresses the critical gap in research concerning the absence of a comparative examination of deep learning models for forest fire detection within G7 nations, as noted in the problem statement. With the primary goal of conducting a concentrated comparative analysis between two deep learning models, CNN and LSTM, for forest fire detection, we investigated their effectiveness in this area. Our findings suggest that while current research largely focuses on image classification methods, there is a lack of detailed consideration for the specific demands of forest fire detection. Through our comparative investigation, we observed that the CNN model demonstrated notably higher accuracy, achieving 0.8798 compared to LSTM's accuracy of 0.8256 in identifying forest fires using image classification. This outcome underscores the CNN model's superiority in this domain, indicating its potential to enhance forest fire detection strategies in G7 nations. Our study offers valuable insights by showcasing the effectiveness of CNN over LSTM, thereby guiding the development of more robust and efficient forest fire detection systems customized to the distinct environmental conditions of G7 countries. Future research could explore further refinements to CNN models or explore alternative deep learning architectures to enhance the accuracy and efficiency of forest fire detection, ultimately reducing the impact of forest fires on G7 nations' ecosystems and communities.

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