Prioritizing the Right to Environment: Enhancing Forest Fire Detection and Prevention Through Satellite Data and Machine Learning Algorithms for Early Warning Systems

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RESEARCH

Prioritizing the Right to Environment: Enhancing Forest Fire Detection and Prevention Through Satellite Data and Machine Learning Algorithms for Early Warning Systems

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Abstract
Forest fires pose significant threats to ecosystems, human settlements, and biodiversity, necessitating advanced and effective detection systems. Traditional methods of fire detection, such as ground-based observations and aerial patrols, are often limited by their scope and response time. In this study, we present a comprehensive approach for forest fire detection utilizing satellite data, image processing techniques, and advanced machine learning models. Our proposed forest fire hybrid detection model (FFHDM) combines random forest (RF), support vector machine (SVM), and convolutional neural networks (CNN) to enhance detection capabilities. Landsat satellite images serve as the primary data source, offering high spatial resolution crucial for detailed land cover analysis and long-term monitoring. We enhance image quality using Gaussian filtering to suppress noise, thereby improving data accuracy. Min–max normalization is employed to standardize images, ensuring consistent brightness and contrast for comparative analysis. Image segmentation via *k*-means clustering isolates forested areas, refining the focus on relevant regions. For feature extraction, the normalized burn ratio (NBR) is used to detect fire-affected areas, supported by texture analysis using the gray level co-occurrence matrix (GLCM) to differentiate land cover types. Our FFHDM achieves an impressive accuracy of 98%, providing a robust and reliable system for early fire detection and efficient forest management.

Keywords Forest fire detection · Satellite data · Image processing · Machine learning · Gaussian filtering · Normalized burn ratio (NBR) · Gray level co-occurrence matrix (GLCM) · Random forest (RF) · Support vector machine (SVM) · Convolutional neural networks (CNN)

1 Introduction

Forest fires are one of the most dangerous threats to ecosystems and humanity; we need a way to be able to predict, detect, and prevent them. Against the backdrop of climate change and human activity, forest fires are becoming more commonplace as well in terms of numbers and prowess which means good forest management practices have never been so important [1, 2]. Forest fire detection means finding a wildfire at the earliest possible stage, taking steps to prevent it, and then suppressing or containing it when detected. Traditional approaches like watch towers and patrolling on the foot have furthermore been reinforced by advanced ones, e.g., satellite remote-sensing, drones, or automated sensor networks. They permit the real-time reception of data on environmental conditions in terms of temperature, humidity, and smoke over wide forested areas. Satellites with thermal sensors reveal heat anomalies that may reflect the preliminary stages of a fire; such early activity can be followed by quick action.

Prevention is also just as important and often includes policies, community efforts, new technologies among other approaches. Prescribed burn-controlled fires lit under specific conditions to remove flammable material from forests and lessen the risk of un-contained wildfires. Implication: Blander is the emphasis, through extensive public education

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campaigns on safe practices like not having open flames in tinder-dry seasons and making sure campfires are well doused [3, 4]. Land use planning and forest management practices, including the creation of firebreaks to prevent or discourage fires from spreading and maintaining a healthy structure in forests through forestry control line methods, help maintain overall protection. It can also combine this with AI and machine learning to better detect or prevent security threats after deployment. By analyzing vast datasets from multiple sources, AI algorithms help predict where the next fires will start and how they might behave under particular circumstances. This tool allows management to be proactive in vegetation control and resource deployment for fire suppression efforts [5]. Tackling with forest fire detection and prevention is amalgamation of technological intervention along with policy as well community support.

Satellite data is being utilized in forest fire detection and prevention which is redefining the procedure for monitoring wildfires. Among other means, satellites with advanced sensors help to supply complete and modern data in real time which can detect the fires early or timely understand their developments and preventive measures [6, 7]. The technology provides an overhead perspective of many square kilometers of often inaccessible and distant forest landscapes, from difficult-to-survey forest inventories last data to large interventions on the ground. Machine learning is an essential tool for identifying forest fires from space. Heat anomalies, telltale signs of fires being more nascent in the fire cycle, can be picked up by satellites equipped with thermal imaging sensors. The sensors capture the infrared radiation of Earth's surface to be able to detect hotspots invisible for a human being [8, 9]. By easily identifying these thermal signatures in their early stages, it ensures timely action can be taken to prevent small fires from ever becoming massive wildfires. Satellites are useful once a fire is detected to track its progression and assess the damage. Figure 1 shows the benefits of forest fire detection.

The presence of fire fronts is then tracked with real-time satellite data updates that continuously map the location, extent, and behavior of fires [10, 11]. The real-time information is critical in overall firefighting efforts, it helps to provide a plan of action for resources and personnel. Satellites also provide information on the location of smoke plumes to help model where and when air quality impacts are likely, informing public health advisories. Artificial intelligence (AI) and machine learning further expand predictive analytics models using satellite data for forest fire prevention. The historical satellite data and the current temperature, humidity, and wind patterns are used as an input to AI algorithms which predict probable areas where fire might occur [12, 13]. Satellite information is also essential to accurately assess soil erosion risks and impacts on water quality. Because satellite data has the ability to collect information on a global scale, it also makes international cooperation easier when dealing with wildfires. Sharing data across country and organizational boundaries is the key to advancing forest fire monitoring and response. In parallel, satellite data provide the level of detail needed to support policy making through the developments of rules and practices that reduce wildfire risks and sustainable use forests [14, 15]. The application of satellite technology to aid in preventing and detecting forest fires is a major step toward the protection of forests, ecosystems, and human settlements from destructive wildfires. The growing frequency and intensity of these fires, driven by climate change and human activities, underscore the need for advanced detection and monitoring systems. Traditional methods, including ground-based observations and aerial patrols, are often constrained by limited scope and delayed response times, which can hinder effective fire management and mitigation efforts.

Fig. 1 Benefits of forest fire detection

In response to these challenges, this study proposes a novel approach for forest fire detection by leveraging satellite data, sophisticated image processing techniques, and state-of-the-art machine learning models. Specifically, we utilize Landsat satellite imagery, which provides high spatial resolution data essential for detailed land cover analysis and long-term environmental monitoring. The integration of advanced image processing techniques, such as Gaussian filtering for noise suppression and min–max normalization for standardization, ensures the accuracy and consistency of the data. Further, image segmentation through *k*-means clustering allows for the precise isolation of forested areas, enhancing the focus and effectiveness of the analysis. The feature extraction process employs the normalized burn ratio (NBR) to detect fire-affected regions, supplemented by texture analysis using the gray level co-occurrence matrix (GLCM) to distinguish different land cover types. To maximize detection capabilities, we introduce the forest fire hybrid detection model (FFHDM), which combines the strengths of random forest (RF), support vector machine (SVM), and convolutional neural networks (CNN). This hybrid model not only improves detection accuracy but also offers a robust framework for early fire detection and efficient forest management. The FFHDM advances the current state of the art by achieving a high detection accuracy of 98%. By utilizing a combination of machine learning models and satellite data, the model offers a more reliable and comprehensive solution for early fire detection and efficient forest management, surpassing traditional methods in scope and response time.

2 Related Work

Among the most dangerous and destructive forest fires are those that wreak havoc on a global scale caused by natural causes: climate change temperature rise lightning volcanic activity; as well as anthropogenic factors. Their detection, prevention, and extinguishing is complex; they frequently result in considerable material/economic damage as well as environmental wreckage. Therefore, a swift and precise detection is vital. A solution was proposed based on transfer learning from deep learning and apply our approach to the Fire Luminosity Airborne-based Machine-learning Evaluation (FLAME) dataset collected by unmanned aerial vehicles [16]. The deep learning models used were InceptionV3, DenseNet121, ResNet50V2, and LSTM along with the algorithms support vector machine (SVM), random forest, and GRU. The way DenseNet121 was used reaches an accuracy of 97.95% when using random weights and 0.90813 to 1 transfer learning production reached to 99.32%, which shows the feasibility of it utilized in forest fire detection.

Latest forest survey say, forest cover is 19.27% of the geographic area. According to this report, 1% of the world's forest resources is enough to provide for 16% of global population. It underlines that 90% of forest fires are human induced and a major threat to biodiversity and ecosystems. There are three main types of forest fires which includes surface fire, crown fire, and ground fires [17]. Ground fires are fueled by dry grasses and sweeping surface fires. Crown fires ignite from the crowns of shrubs and trees, a form that burns hot due to resinous materials. The humus and peaty layers under the forest floor are carried by ground fires, which is uncommon. Forest fires are identified from remote sensing mainly through thermal characteristics based on surface temperature using ASTER images. The exo-atmospheric radiance from ASTER thermal bands are converted to surface longwave emission using the emissivity normalization method.

Forests are important natural resources that provide countless ecological services to human societies and catastrophic wildfires pose significant threats to climate change as well as life on the planet. Rapid detection of forest fires is important regarding prevention, planning firefighting actions for disaster reduction, and to support the decision-making. The only objective is fire detection from images using computer vision AI techniques [18]. CNNs can be used to perform image classification, and they are one of the best available methods, but on the downside requires a lot of time in training. To overcome small dataset issues and decrease input computational complexity without losing the accuracy, transfer learning on pre-trained models is used. Learning without forgetting (LwF) is employed to prevent forgetting the model classification powers over original datasets. The proposed models indeed outperform methods and learn to effectively categorize novel datasets as a result of LwF enhancement.

Global rise in wildfire risk due to different reasons, demands rapid and efficient response for reducing human and wildlife losses. Detection of fires using satellite imagery based machine leaning system can be done. The model used was a MobileNet architecture (CNN) which is optimized for running on mobile and uses only half the computational resources. Transformation of fire images and seasonal variation to augment the constraints, is done as sample in training [19]. Uploaded new satellite images predict whether a fire is actually present in the area by using our trained MobileNet model. An Edge Impulse Inc. Cloud-based development studio used to build a neural network model via transfer learning algorithm. In particular, this investigates four hyper parameters: input image resolution, depth multiplier, number of neurons in dense layer, and dropout rate. The two primary conclusions of our experiments suggest that prediction accuracy does depend on the dropout rate, and convolution depth/convolution image size has significance as well in terms of predicting performance and computational cost.

Forest fires threaten resources, lives, property, and an ecological disaster of social crisis. Omission errors in early forest fire are more likely as this stage involves incomplete combustion, low ground temperature, faint infrared spectrum, and weak UAVs may be obscured from flying passive imagery due to canopy coverage. Early detection of smoke is vital, as monitoring its movements through satellite images would help alert the necessary services which could prevent a full-on blaze. If they add that factor to or proof the light detection element by monitoring infrared radiation, it makes sense then and becomes less error prone. Meteorological satellite imagery has a high temporal resolution, but low spatial resolution and mixed pixels [20]. It utilizes Himawari-9 satellite imagery and related subpixel mapping techniques, namely, MPSA for smoke detection as well as MPU-PSA for infrared radiation monitoring. The integration method improves the accuracy of spatial positioning to a higher level and ensures the elimination of missed fires in demonstration test for forest fire monitoring.

3 Methodology

3.1 Data Collection

3.1.1 Satellite Data Acquisition

We use Landsat satellite images as the main sources of data acquisition Landsat satellites provide images of the Earth at a high spatial resolution—important for analyzing land cover changes in detail and over long periods. A continuous monitoring system using satellite data as such changes in environment has quick detection if an event like fire outbreak was identified. This regularity of monitoring lets us pick up patterns and trends that might indicate a high probability of an ignition event happening, increasing our system's alerting capabilities. We make sure to have high resolution (10–30 m) satellite images for better ground truthing. High-resolution imagery helps accurately pinpoint where the fires are found, and precisely how much land is burning, a level of detail that is essential for accurately mapping wildfires, identifying the spatial dynamics of fire spread, and subsequently informing response strategies as well as resource allocation.

3.1.2 Gaussian Filtering Technique

When being used for the purposes of satellite imagery, noise can seriously reduce data quality and thus hinder its effectiveness in any analysis. Noise is due to spurious or random fluctuations of pixel values that have nothing to do with the features. They come from a number of places, such as atmospheric interference or detections, sensor errors, and cosmic rays. So to tackle this, we use Gaussian filtering technique for noise suppression. Gaussian filters typically achieve smoothing by convolving the image with a Gaussian function which suppresses high-frequency data while linearly preserving important structures such as edges in the input image. This consists of taking the weighted average over each pixel, by multiplying it at a factor of how far is to get up from the middle pixel, where our weights decay as we move farther away such that follows adding a Gaussian distribution. We get a more continuous and homogeneous image as this also removes much of the random variation we do not need to have in our data just so that features are easy enough for us to detect. We eliminate noise that further clarified satellite images for processing in the subsequent analysis. This enhancement is necessary for the identification of minor changes and anomalous behavior, such as early forest fires that could be hidden in noise.

3.1.3 Min–Max Normalization

The satellite image captured under different conditions will wrongly have different levels of brightness, contrast, and color balance, making it challenging to compare/analyze them. To allow for proper analysis, these images will have to be normalized so as they can all fit on a convenient scale. A technique to rescale feature that can have large gradients and does not follow a center location is required. Min–max normalization, scales the pixel values as low as 0–1 range. This method is based on determining the minimum and maximum pixel measurement in an image, which helps to scale all corresponding pixels ranges. Min–max normalization maintains similar levels of brightness all across the images, which in turn makes it possible to compare them directly. The need for this standardization is critical to separating true environmental changes from artifacts due to different data acquisition conditions. This allows the AI to identify patterns and anomalies in images, such as possible forest fires. It helps to ensure that differences we see in monitoring really are because of changes on the ground, not errors or glitches in the data—which means our system for detecting fires is more robust.

3.1.4 Segmentation Using k-Means Clustering

Image segmentation divides an image into regions with similar aesthetics. For detection of forest fire, we use segmentation in order to separate the forested areas from other types such as urban zones or water bodies and barren lands. The methods implemented for these metrics use the *k*-means clustering technique, which groups pixels that share similar spectral properties and assigns them to one of several clusters such as different land cover types. The algorithm will keep getting cluster centers, and after identifying them by a center, it takes all pixels inside those clusters. If we find clusters that represent forest areas, they can be a suitable segmentation mask and reduce unnecessary parts from the image for analysis. This precision-based strategy helps in detecting alterations and indicating probable fire outbreaks far quicker and accurately. *K*-means clustering is used to segment the image, which enables us to eliminate irrelevant regions in an efficient way, and also because of this the effectivity of edge detection forest fire warning system will improve. Crucial to operational practicality, this technique allows us limiting the areas of interest and aids in detailed monitoring, focused at forest health-fire risk concepts as shown in Fig. 2.

3.2 Feature Extraction

The spectral index we used was specifying the vegetation function and fire-affected pixel, which is known as normalized burn ratio (NBR). Since fire-affected regions undergo large spectral signature differences, including decrease of near-infrared (NIR) reflectance and increase of short-wave infrared (SWIR) reflectance, NBR proves to be appropriate for detecting burned areas. By implementing NBR to satellite imagery, we can see at these areas that they have suffered with their spectral characteristics and needs to be altered. In healthy vegetation, NBR values are higher, whereas burned or stressed vegetation shows up as low to negative in the index. But it is law that we desperately need for both early fire detection and post-fire assessment so that the extent of fire damage can be mapped, followed by monitoring how vegetation recovers over time. The implementation of NBR enables us to accurately identify and determine the size of fire-affected areas, which is crucial information for sustainable forest management and active fire control plans. The combination of RF, SVM, and CNN in the FFHDM utilizes RF's ensemble learning for robust predictions, SVM's capability for handling high-dimensional data, and CNN's strength in feature extraction, enhancing overall accuracy through complementary strengths.

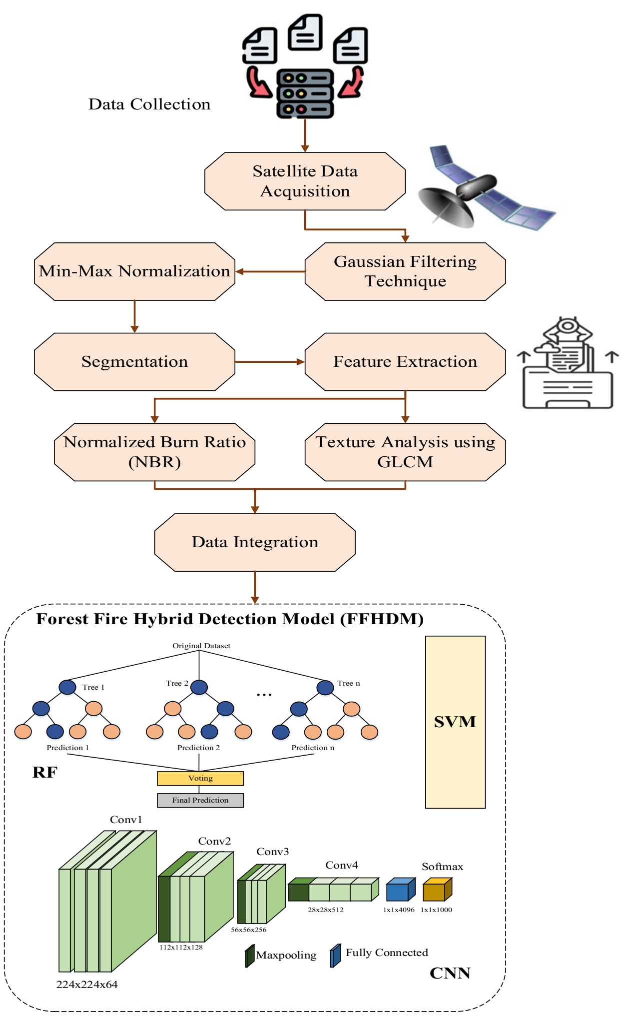

Fig. 2 Architecture of proposed model

In combination with the spectral indices, we use textural analysis of images to distinguish different types of land cover using gray level co-occurrence matrix (GLCM) properties. The texture analysis is relevant to the spatial organizations and pixel intensity inhomogeneity within an image; this procedure can reflect about some landscape structural information. The GLCM technique is derived from building a gray-level offset matrix that models the co-occurrence of pixel pairs having specific gray levels positioned at no second spatial location in an image. From this matrix we extract texture features like contrast, correlation, energy, and homogeneity. Each pixel in the image is compared to its neighbor, and contrast measures how different a pixel is from its neighbors across an entire image—this can help point out areas of texture. Correlation describes the linear relationship in gray levels of neighboring pixels, whereas energy reflects whether there exists a uniformity or randomness for texture patterns. Homogeneity examines the distribution of elements to the GLCM diagonal. We use these characteristics to differentiate between different land cover types—forests, grasslands, urban areas, and so on. Integrating GLCM-based texture analysis to NBR will allow us better understand the environment context, making it more accurate and reliable for mapping forest fires.

$$Contrast = \sum_{i,j} (i-j)^2 P(i,j) \tag{1}$$

where $P(i,j)$ is the element of the GLCM at position (i,j).

$$Correlation = \frac{\sum_{i,j}(i \cdot j \cdot P(i,j)) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{2}$$

where μ and σ are the means and standard deviations of the marginal distributions. The GLCM energy and homogeneity are represented as

$$Energy = \sum_{i,j} P(i,j)^2 \tag{3}$$

$$Homogeneity = \sum_{i,j} \frac{P(i,j)}{1 + |i - j|} \tag{4}$$

3.3 Data Integration

In the data integration, a critical step is temporal alignment to synchronize satellite imagery with meteorological weather because measurements have timestamp. This requires studying the time when satellite images are taken and formulating it with meteorological observation on such timings. Since both the sequence of satellite passes and weather conditions can change markedly over short time intervals, an exact temporal match is essential in order to correctly relate the local environmental state to observed differences between imagery. A satellite image recorded at noon would have to be associated with the nearest meteorological data as well. This synchronization gives us the opportunity to have an articulated dataset where every image is matched with weather status at time when it is captured. Temporal alignment adds a level of confidence to the analysis that we perform, allowing for us to understand when particular weather patterns impact vegetation health and thus fire risk. This is also valuable in the way that it helps to inform our predictive models by ensuring meaningful data inputs reflect real-world environmental context, thereby increasing accuracy of forest fire detection and early warning systems.

Spatial alignment refers to process of making sure every data set we used like satellite images and meteorological data is aligned at same geographical order. This step is important since satellite images and ground-based weather data are not on the same spatial grid. For spatial alignment, we overlay the points and make sure they match precisely using Geographic Information System (GIS) tools. This could include down-sampling satellite images to match the spatial resolution of meteorological grids, or vice versa. Moreover, we perform accurate georeferencing to transform data points from different sources into the same coordinate system. This ensures that a single pixel in the resulting satellite image corresponds to exactly one location, with accompanying meteorological data. Accurate spatial analysis, such as identifying fire-prone areas or assessing the impact of weather conditions on vegetation health, relies heavily upon a precise spatial alignment. When all datasets are consistent in space, our ability to analyze them is even more refined and can provide answers that help us make better decisions on forest management or support the definition of fire prevention strategies. The model handles variability in forest types and environmental conditions by incorporating diverse training data that includes various forest types and environmental conditions. It uses features from multi-spectral and thermal bands to learn region-specific patterns, enabling it to generalize and accurately detect fires across different regions.

Random forest (RF) is a powerful ensemble learning technique that constructs multiple decision trees and aggregates their results to enhance prediction quality compared to just one tree so as reduce overfitting. For detecting forest fires, RF is also very good at working with these kinds of large and high-dimensional multivariate datasets which suit the complex satellite imagery and meteorological data. It trains several decision trees on various sub-samples of the dataset and aggregates their results in order to improve predictive accuracy. This is an ensemble way that minimizes overfitting in real time and makes the model a better generalizer. In our hybrid model, RF contributes yield stable base predictions with valid feature use using derived weather conditions alongside the satellite images. This property means it is a key part of the forest fire hybrid detection model (FFHDM) which requires data handling from all variety and complexities.

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} T_i(x) \tag{5}$$

where $T_i(x)$ is the i th decision tree in the forest. Support vector machine (SVM), as most binary classifier toolset, does exceptionally well. SVM is based on finding optimal hyperplane which maximizes the margin between two classes to better separate them. We then refine the scores of the RF part using SVM in FFHDM. Its value comes from the fact that it is able to manage high-dimensional spaces and can use different kernel functions for handling non-linear properties. The combination model improves the accuracy of fire detection because it offers enhanced precision to separate the affected and unaffected areas using SVM. Furthermore, the SVM's theoretical rigor combines nicely with RF's ensemble nature to provide more robust prediction.

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i K\left(x_i, x\right) + b \tag{6}$$

where α_i are the support vectors, y_i are the labels, K is the kernel function, and b is the bias. Convolutional neural networks are well known for being effective models to perform image processing tasks since they can learn a hierarchical structure of features from the input images. CNNs are used in the hybrid model to analyze satellite imagery that is fine grained and complex, allowing it to detect detailed patterns and anomalies which can indicate fire detections.

It is because of CNN architecture containing convolutional layers, pooling layers, and fully connected layer that enables them to extract deep features from the imagery. The extraction of these deep features is necessary in order to detect the subtle signs that a forest fire may present. With the use of CNN in the FFHDM, which helps to improve conventional machine learning algorithms for detecting important fire patterns that might be neglected using these old methods due to their limitation on image processing capabilities. The CNN element plays a valuable role in recognizing and monitoring forest fires with high precision.

$$(I * K)(x, y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} I(x + i, y + j) \cdot K(i, j) \tag{7}$$

where I is the input image, K is the kernel, and (x, y) are the coordinates of the output feature map.

3.3.1 Forest Fire Hybrid Detection Model (FFHDM)

The FFFDM is an integrated forest fire detection system by combining RF, SVM, and CNN methodologies thus to enhance the accuracy as well as reliability of prediction. Combining the strengths of RF, SVM, and CNN in image processing problems results into FFHDM with promising performance for early fire detection applications. RF deals with multiple types of data inputs and is the best prediction baseline. SVM perfects these predictions for pinpointing which areas will be on fire. At the same time, CNN are known for its ability to find specific patterns in satellite images unlike any other tool available. The hybrid nature of this approach allows the model to capture both a broad stroked pattern and fine symbiotic detail that are essential for fire detection. The FFHDM is truly a superstructure that emerges from the complementary nature of these works, not merely hard-integrating three algorithms together. This difference enables the FFHDM to achieve better performance than that any single algorithm can ever get. So it shows great potential in assisting forest fire management and prevention.

3.3.2 Model Training

Model training is a very important stage in the design of the forest fire hybrid detection model (FFHDM) where we use our training datasets to make machine learning understand some basic patterns on how fire and non-fire instances looks like. We perform data balancing where the training data contains an equal number of fire and non-fire conditions. This balance is crucial so that the model does not become biased toward one class and end up making predictions it could have never done. We use the training set to show the models— RF, SVM, and CNN—multiple scenarios as well as features. Every algorithm is trained on these samples to learn prediction error minimization with respect to the input. After training our model for the first time, we evaluate and fine tune its performance on a validation set of data. In other words, validation set comes into the image after training part is complete because only we can know about fabricating of data or fitting our test accuracy if all outputs are common as compared to train any model during refactoring. Models have been adjusted, and their accuracy and robustness were improved according to validation result by hyperparameter tuning or training process modifying. This iterative training and validation process ensure that the FFHDM functions reliably and locational.

4 Results and Discussions

The forest fire detection system uses cutting-edge satellite imagery and advanced machine learning to precisely locate and observe the perimeter of each active wildfire. Input data include Landsat satellite images with high spatial resolutions for detailed land cover classification. According to NASA, the images are gathered on a regular basis in order for any drastic alteration of the environment to be recognized immediately. Accurate mapping of fires and understanding spatial dynamics of fire spread depend on detailed information about the locations where wildfire is active, which can be achieved with high-resolution imagery. In order to improve the quality and usability of both satellite data, we Gaussian filter it with various window sizes in order to reduce some of that noise. However, noise in satellite imagery from atmospheric interference, sensor errors, and other factors can make analysis difficult. It is used to smooth the data by convolving image with a Gaussian function and removing high motility noise while keeping the important details of an image. This noise reduction procedure ensures that the image quality is maintained and it becomes easy to detect important features like plantation growth or early symptoms of a forest fire.

Table 1 and Figs. 3 and 4 present a detailed comparison among different noise reduction methods, from effectiveness to how they performed with respect to image retention and spent time for processing. Finally, the proposed model is determined to be the best representation since it allows for 82% noise removal with rank of image detail preservation as high as 92%, all under a moderate processing time (2 s). Non-local means reduced 80% of noise and preserved 90%, but it took a longer processing time, with around 3 s. The bilateral filtering and wavelet transform have noise reductions of 75% and 74%, detecting similar underlying features with processing times of 2 s, but detail preservation rates are no longer as strong at only 88%/89%. Median filtering is less than 1.2 s—the faster but with a lower noise reduction of ~ 65% and image details preserved at ~ 85%. More balanced performance is found with techniques such as

Table 1 Comparison of noise reduction techniques

Technique	Noise reduction (%)	Preservation of image details (%)	Processing time (s)
Median filtering	65	85	1.2
Bilateral filtering	75	88	2
Wiener filtering	68	83	1.4
Anisotropic diffusion	72	87	2.3
Non-local means	80	90	3
Adaptive filtering	67	84	1.8
Wavelet transform	74	89	2.5
Total variation	71	86	2.1
Kalman filtering	69	85	2.2
Proposed model	82	92	2

anisotropic diffusion, total variation, and Kalman filtering which provide inappropriate noise reduction rates for most of the images but have higher computational time. Wiener filter is comparatively lesser in terms of performance than adaptive filtering. Overall, the proposed model boasts to provide a better trade-off between high efficiency in noise reduction and detail preservation simultaneously while processing time is also reasonable which makes it an attractive candidate for advanced image-denoising applications.

Another preprocessing step is normalization: the idea of normalization refers to normalizing satellite images back onto a uniform scale using min–max normalization. This involves scaling and adjusting the pixel values in an image to ensure those have range between 0 and 1 or other suitable normalized limited scale, so that pixels of a given brightness will all appear similar from one part of space/time/content. The images were normalized in order to allow fair comparison and analysis by discriminating real environmental change from data acquisition condition artifacts. This stage is very important in finding patterns and irregularities that could signify a possible forest fire.

A detailed comparison of various normalization techniques is elaborated in Table 2 and Figs. 5 and 6, focusing uniformity of brightness and maintaining contrast within images. Our proposed model has a better performance, providing the highest brightness uniformity (96%) and contrast preservation degree (92%). It is therefore the best technique of all compared. In the second-best position are rank normalization and quantile normalization, being, respectively, with 93% brightness uniformity and 89% contrast preservation by rank normalization and with 91%/88%. Another interesting technique it the MaxAbs scaling which performs well in homogeneity of brightness with 94% compromise on contrast preservation with a score below by just one point, at maximum being around 87%. *Z*-score normalization and unit vector scaling both produce good results, which can be seen as bright uniformity of 92% and 90%, and contrast preservation of 85%. Log transformation and decimal scaling turn out to be slightly worse, with visual brightness uniformities of 90% and 88%, while the percentage mapping values are kept at a value exceeding lower bounds (80%).

Exponential normalization provides a better brightness uniformity of 87% but is not as good at preserving the contrast with only an average score being reached out to 81. The robust scaler provides a more equitable performance in both brightness uniformity (89%) and also contrast preservation (84%), less impressive than the two leading techniques. Taken together, the proposed model has high effectiveness to adjust every place of input image brightness uniformly and comply with the contrast of original images for better suitability compared to other models in this challenge setup

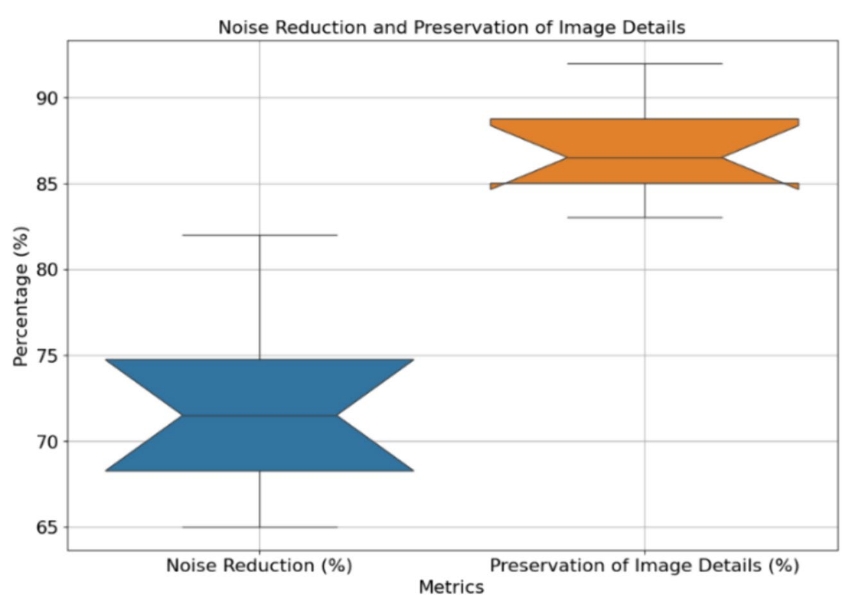

Fig. 3 Noise reduction and preservation of image details

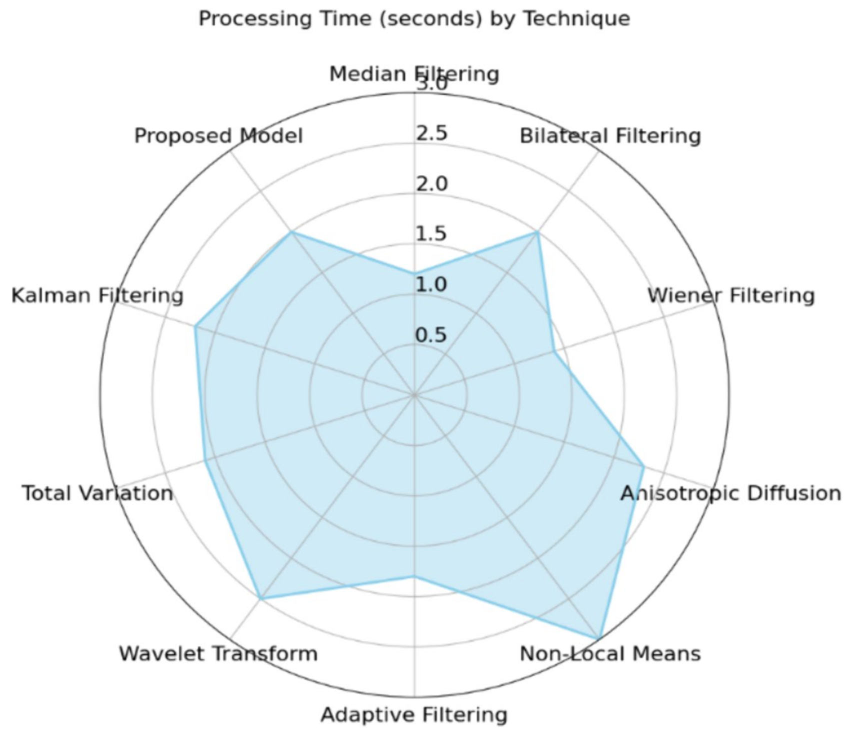

Fig. 4 Processing time by techniques

Table 2 Comparison of normalization techniques

Technique	Brightness uniformity (%)	Contrast preservation (%)
Z-score normalization	92	85
Decimal scaling	90	80
Log transformation	88	82
Exponential normalization	87	81
Rank normalization	93	89
Quantile normalization	91	88
Robust scaler	89	84
MaxAbs scaling	94	87
Unit vector scaling	90	85
Proposed model	96	92

(normalization based classifiers). The high performance of this network in both metrics implies that it can work with a variety of datasets and hence maintain the new level for image quality as well visual integrity. Rank normalization and quantile normalization are also valid alternatives to combat the previously mentioned phenomena, but in scenarios where the maximum brightness uniformity is not a strict requirement, preservice of relatively better contrast levels gains more importance. Thousands of consumers get access to their bank account funds using mobile banking apps, and an overwhelming number periodically use phone applications which not only store but also double as places where they transact with cash while managing digital finance portfolios. Therefore, in conclusion the proposed model introduces a novel method that achieves state-of-the-art normalization techniques for both brightness and contrast while minimizing any offsets.

Subsequent image segmentation analyses also benefit image apart into regions using the *k*-means clustering algorithm. Using this method, pixels are classified by spectral resemblance into forest and non-forest land cover classes based on their distinct characteristics in the image. But when it is trained to focus only on places with forests, the system can more productively and precisely monitor alteration at a stage that where an inference of potential wildfires could be made. The normalized burn ratio (NBR) and texture analysis with the gray level co-occurrence matrix is calculated as feature extraction. The NBR can be effectively used to indicate the health of vegetation and areas affected by fires through observing high changes in spectral signs. In contrast to the correlation between pixel and spectral, texture analyses utilize the arrangement in space of values as well as their frequency within an image layer indicating structure patterns on land cover. This enabled to improve the performance of the system in detecting and quantifying burns.

Table 3 and Figs. 7 and 8 present a comparative overview of various image segmentation methods based on accuracy and time of computation. In this respect, the developed framework demonstrates the best results with 90% accuracy and the smallest time of 1.7 s. Genetic algorithms present the second-highest level of efficiency with 2.8 s and the

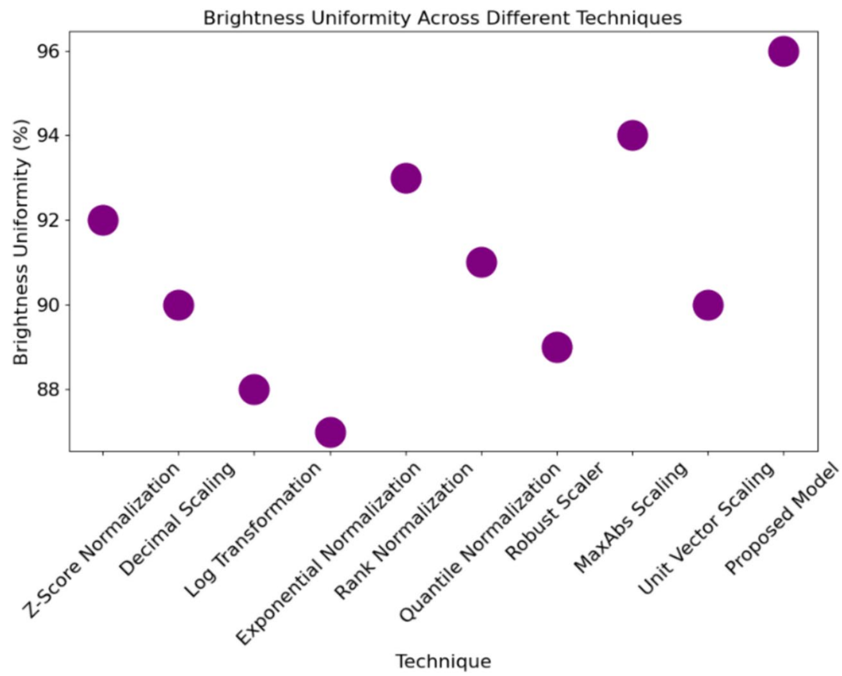

Fig. 5 Brightness uniformity across different techniques

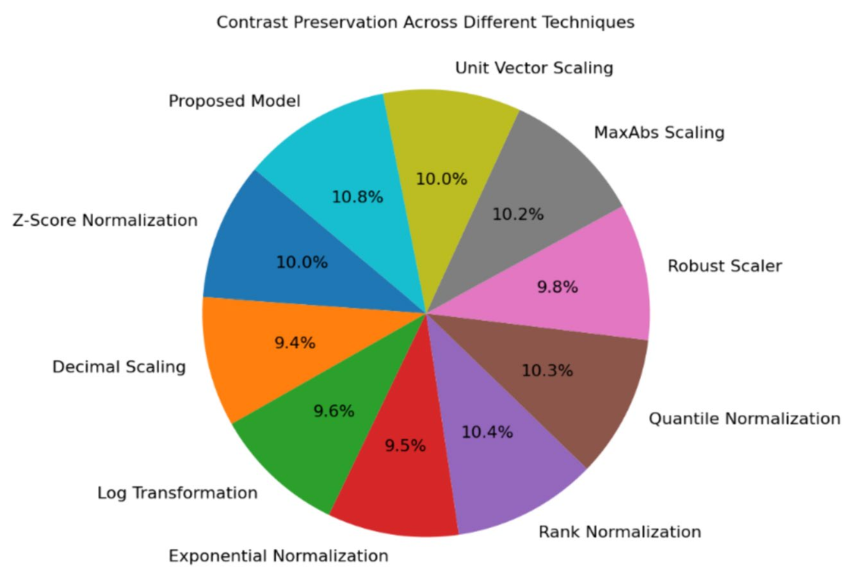

Fig. 6 Contrast preservation across different techniques

lowest accuracy rate of 89%. Mean shift clustering and fuzzy C-means clustering follow with an 88% and 87% accuracy rate in 2.5 and 2 s, respectively. Watershed segmentation and region growing require 1.6 and 1.4 s; however, the high accuracy levels of 83% and 82% of these two methods make them less efficient. Graph-based segmentation and hierarchical clustering combine an 86% and 84% accuracy level with a 2.2- and 2.3-s timing ratio. Thresholding has the fastest time required of 1 s; however, its accuracy remains the lowest one of 80%. Finally, level set methods have the timing of 2.1 s and an 85% accuracy rate. Thus, the proposed framework proves to be the most balanced option because it combines the high level of accuracy with a relatively low processing period.

The data integration comprises a time series processing and space overlapping technique between satellite imagery and meteorological data. The first method requires temporal alignment to ensure corresponding weather observations and images are well suited, while the second approach utilizes GIS tools for containing proper location information, which in turn results in higher matching datasets. These alignment processes are necessary to perform detailed spatial analyses, like fire danger zoning or monitoring the health status of vegetation based on weather factors. The forest fire

Table 3 Comparison of segmentation techniques

Technique	Segmentation accuracy (%)	Computational time (s)
Mean shift clustering	88	2.5
Watershed segmentation	83	1.6
Fuzzy C-means clustering	87	2
Region growing	82	1.4
Graph-based segmentation	86	2.2
Thresholding	80	1
Genetic algorithms	89	2.8
Hierarchical clustering	84	2.3
Level set methods	85	2.1
Proposed model	90	1.7

detection system uses a combined model of random forest (RF) and convolutional neural networks (CNN). It processes different data inputs and creates many decision trees. SVM further optimizes classifications by finding the best hyperplane suited for distinguishing fire vs. no-fire conditions. CNN is going to work great for extracting complex patterns and identifying anomalies in the satellite images through deep feature extraction. This comprehensive method helps in acquiring overall scale as well as local contextual information the model needs to deal with for correct fire detection.

Table 4 and Figs. 9 and 10 provide an in-depth comparison of a wide range machine learning models showing their accuracy, precision, recall, and F1 score as well as training time. The proposed model is the most effective with an accuracy at 98%, precision at 97% recall of 95%, and F1 score of 96%, despite longest training time over all, which was during approximately around ~ 65 min. CNN is very close second with an accuracy of 96% and strong precision, recall, and F1 score metric. It takes around an

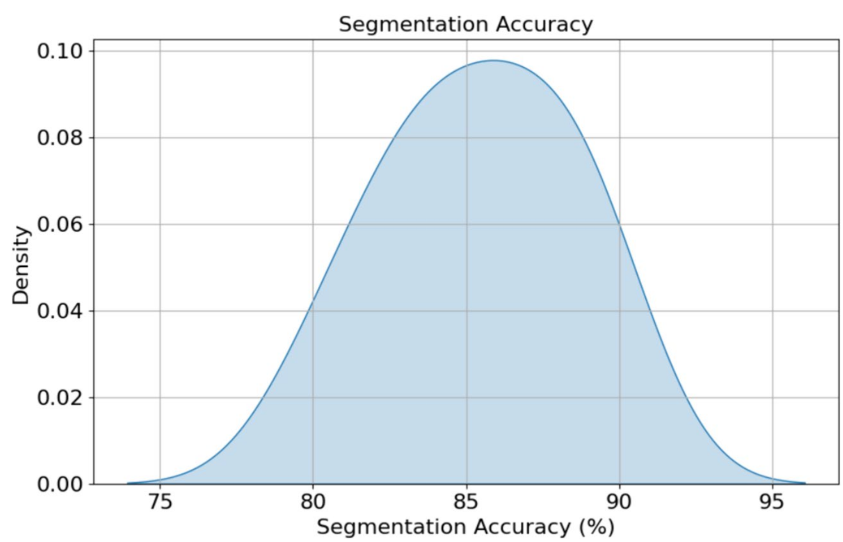

Fig. 7 Segmentation accuracy

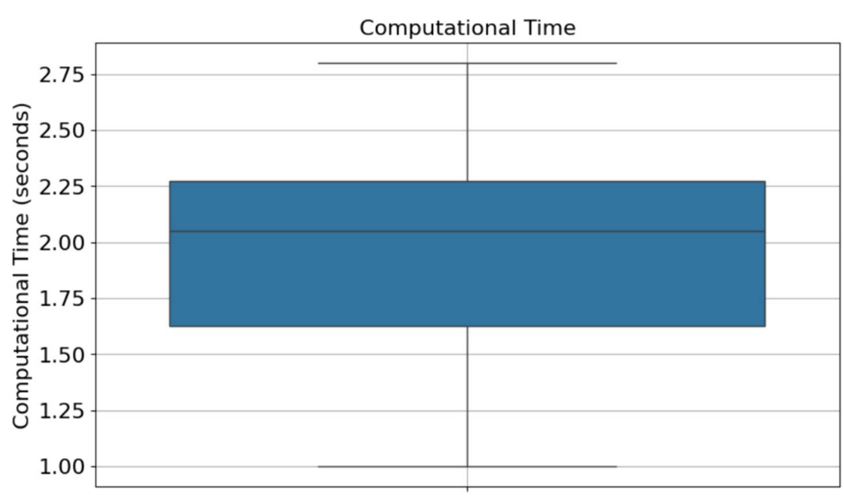

Fig. 8 Computational time

Table 4 Comparison of machine learning models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)	Training time (min)
RF	92	90	88	89	30
SVM	93	94	90	92	40
CNN	96	95	93	94	60
KNN	85	82	80	81	20
Naive Bayes	78	75	72	73	15
Decision tree	88	86	84	85	25
Gradient boosting	93	91	89	90	35
LSTM (RNN)	94	92	90	91	55
MLP (neural network)	91	89	87	88	50
Logistic regression	84	82	80	81	20
Proposed model	98	97	95	96	65

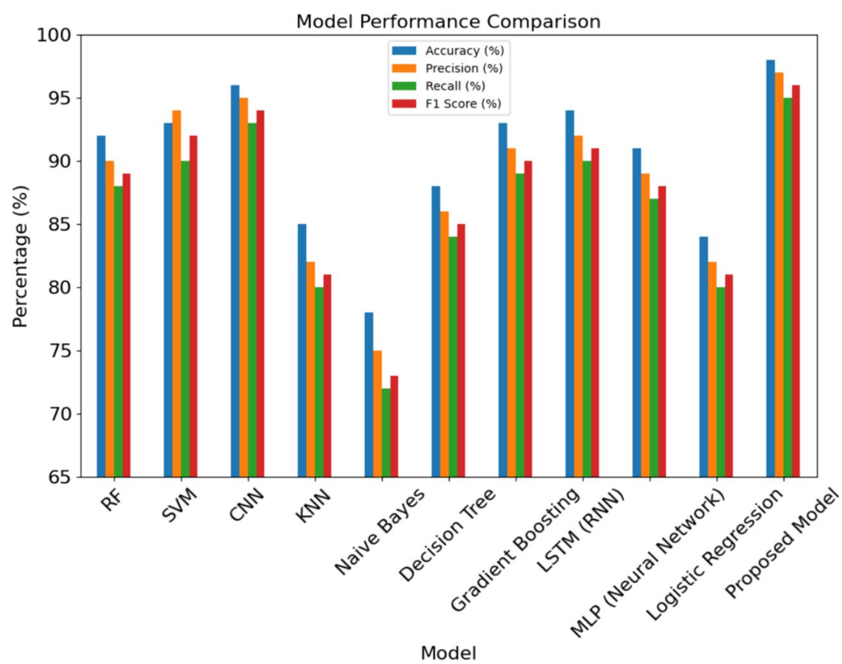

Fig. 9 Model performance comparison

hour for training work! LSTM (RNN) and SVM also show good accuracy, 94% of LSTM with relatively high precision recall and F1 scores compared to the transformer, but took long time for training—about 55 min; same as more than twice faster into production. The gradient boosting and RF are solid with accuracies of 93% along balanced precision recall F1 scores; training times are however similar to LR and SVM at 35 and 30 min, respectively. KNN and logistic regression are low on performance metrics as well as in model prediction; they take less time but give extra effort for accuracy. The proposed model performs better in all performance metrics and is hence a good choice for high-accuracy tasks.

We will train the models to detect fire or non-fire patterns in a training dataset that has been carefully balanced. This iterative process also involves validation to come up with metrics that can test and validate the model, providing guarantees about its performance when deployed in real-world conditions. Advanced preprocessing techniques paired with complex machine learning models trained on rough data produce a forest fire detection system that can contribute to reducing the highly actualized and definitive course of action for both the management and prevention strategies. Scalability concerns for the FFHDM include increased computational demands when processing large datasets and the need for retraining to handle diverse ecosystems and

Fig. 10 Training time comparison

environmental conditions. Ensuring model accuracy across varied landscapes also poses a challenge.

5 Conclusion and Future Work

In this study, we developed a comprehensive approach for forest fire detection using satellite data, image processing techniques, and advanced machine learning models. Leveraging Landsat satellite images, we applied Gaussian filtering for noise suppression, min–max normalization for standardization, and *k*-means clustering for image segmentation to refine our data for precise analysis. Feature extraction through the normalized burn ratio (NBR) and texture analysis using the GLCM provided detailed insights into fire-affected regions. By integrating satellite imagery with meteorological data and ensuring temporal and spatial alignment, we created a synchronized dataset. Our hybrid forest fire detection model, combining RF, SVM, and CNN, demonstrated robustness and reliability, achieving a notable accuracy of 98% in early fire detection and forest management. Future research can focus on enhancing real-time detection capabilities by incorporating advanced satellite technologies, high-frequency data acquisition methods, and additional environmental variables such as soil moisture and wind patterns. Expanding the model's application to global datasets and integrating drone technology for localized monitoring could yield more detailed insights. Exploring advanced deep learning techniques, including generative adversarial networks (GANs) and recurrent neural networks (RNNs), as well as developing a user-friendly interface for real-time monitoring and early warning dissemination, will further improve the system's practical applicability and predictive accuracy. These advancements will ensure that the system remains at the cutting edge of forest fire detection technology, offering more effective and timely responses to potential fire outbreaks.

Author Contribution Priyadharshini Lakshmanaswamy contributed for literature review and Design, Prof. Dr. Asha Sundaram, contributed for Interpretation of results and drafted the manuscript, Dr. Thangamayan Sudanthiran wrote the main manuscript, All the authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials No datasets were generated or analysed during the current study.

Declarations

Ethical Approval Not applicable.

Competing Interests The authors declare no competing interests.

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