**Title Page:**

Forest fire detection using Novel Feedforward Neural Network in comparison with Convolutional Neural Network with enhancing accuracy

Varun M1

Department of Computer Science Engineering,

Saveetha School of Engineering,

Saveetha Institute of Medical and Technical Sciences,

Saveetha University, Chennai, Tamil Nadu, India, Pincode: 602105.

192111007.sse@saveetha.com

S.Kalaiarasi

Project Guide, Corresponding Author,

Department of Cyber Security,

Saveetha School of Engineering,

Saveetha Institute of Medical and Technical Sciences,

Saveetha University, Chennai, Tamil Nadu, India, Pincode: 602105.

**Keywords:** Multispectral imaging system, FNN Algorithm, Early fire detection, Artificial Intelligence, CNN Algorithm.

**Abstract:**

**Aim:** The objective of this project is to enhance the accuracy of forest fire detection, by comparing the performance of the FNN algorithm with a CNN algorithm. **Materials and Methods:** To improve the accuracy of Forest fire detection is implemented by using the FNN algorithm with a sample size of (N=20) and CNN algorithm (N=20) with a G power of 80%.**Results:** The Forest fire detection through the FNN algorithm gained an accuracy of 93.4% whereas the CNN algorithm obtained an accuracy of 87%. There is a statistically significant difference between the FNN algorithm and the CNN algorithm with (p=0.000) (p<0.05). **Conclusion:** The Forest fire detection is implemented using the FNN algorithm and compared with the accuracy of the CNN algorithm. From the findings, it is evident that the FNN algorithm appears to be better than CNN.

**Keywords:** Multispectral imaging system, FNN Algorithm, Early fire detection, Artificial Intelligence, CNN Algorithm.

**Introduction:**

Infrastructure, human lives, and biological systems are all constantly at risk from forest fires. There have been several incidents of wildland and forest fires in the past[(Saleh et al. 2024)](https://paperpile.com/c/S6cZKE/30qir). It is amazing how much fires influence the layout and structure of landscapes and, ultimately, the species composition of ecosystems[(Lertsinsrubtavee, Kanabkaew, and Raksakietisak 2023)](https://paperpile.com/c/S6cZKE/RojhV). The formation of plant communities, the availability of nutrients in the soil, and biological variety are the governing elements that form an intrinsic part of the ecological role of forest fires[(Saydirasulovich et al. 2023)](https://paperpile.com/c/S6cZKE/56pP0). Despite jeopardizing human lives, fires are regarded as a major environmental problem due to the substantial ecological and economic harm they do [(Lin et al. 2024)](https://paperpile.com/c/S6cZKE/nKs5P).

Traditional fire safety methods use mechanical devices or human observers to monitor the surroundings[(Bhagwat et al. 2023)](https://paperpile.com/c/S6cZKE/g78AH). Particle sampling, air transparency testing, and temperature monitoring are frequently the most widely used techniques for identifying fire smoke[(Hoehler et al. 2023)](https://paperpile.com/c/S6cZKE/jS2Aj). No alert is sounded until the particles reach the sensors and cause them to become active. Worldwide, forest fires are becoming more frequent as a result of climate change. These occurrences pose a serious threat to human safety in addition to causing large financial losses and ecological devastation.

Forest fires typically spread swiftly and are challenging to put out quickly[(Lee and Jaffe 2023)](https://paperpile.com/c/S6cZKE/MwA3X). As a result, it is crucial to find forest fires early on before they spread, but there are clear disadvantages to using conventional detection techniques when dealing with wide forest areas[(Wang et al. 2023)](https://paperpile.com/c/S6cZKE/gvoV). Although sensor-based detection systems work well indoors, installing them outdoors is challenging because of the high cost of coverage[(Lindenmayer and Zylstra 2023)](https://paperpile.com/c/S6cZKE/37fyy). Furthermore, they are unable to offer crucial visual data that would enable firefighters to quickly assess the state of the fire scene[(Gorta et al. 2023)](https://paperpile.com/c/S6cZKE/gTDfW).

**Materials and Methods:**

Finding the ideal sample sizes for forest fire detection was the main focus of a study carried out at the Saveetha Institute of Medical and Technical Sciences' Department of Computer Science Engineering. The selection process was directed by Gpower software, resulting in the selection of two groups, each containing 40 sets of samples, for a total of 40 samples. Using IBM SPSS software version 26, sample size calculations were performed with the following G-power parameters: 80% protest power, 95% confidence level, alpha at 0.05, beta at 0.2, and power of 0.8.

Technical Analysis software was used to novel feedforward neural (FNN) and convolutional neural network (CNN) algorithms. Windows 10 OS was used as the experimental setup, and Python OpenCV software was used. Hardware specifications included an Intel Core i3 CPU running on a 64-bit OS and 4 GB of RAM. Images made up the dataset used to detect forest fires. Key spots and regions were identified utilizing counter vectors and predetermined threshold values in detection procedures.

The study implemented Python as the primary programming language for coding, conducting an independent T-test analysis to validate both methods. To test image-based attack detection classification, a dataset was sourced from Kaggle. Enhancing precision involved scrutinizing variables serving as either independent or dependent factors in the analysis.

**Novel Feedforward Neural Network(FNN)**

An innovative architecture for a feedforward neural network (FNN) is suggested and examined. This recently established feedforward neural network (FNN) model is different from standard feedforward neural networks in that it has novel structural alterations and activation functions that are intended to improve learning capabilities and task performance. Deeper network topologies can be made possible by the FNN architecture, which makes feature extraction and representation learning more effective. This study, which aims to advance the field of neural network architectures for better modeling and prediction tasks, investigates the effectiveness of the novel FNN in solving complex problems by utilizing its capacity to learn intricate patterns and relationships within data through rigorous experimentation and analysis.

**Algorithm for Novel Feedforward Neural Network(FNN)**

Step 1: Library Imports and Setup

Step 2: Dataset Handling and preprocessing

Step 3: Perform Model Architecture

Step 4: Perform Model Training

Step 5: Perform Model Evaluation

Step 6: Calculate the accuracy and loss on the validation set, printing the results.

**Convolutional neural network**

Convolutional neural networks, or CNNs, are strong deep learning architectures that are frequently used for tasks involving image processing and recognition. A CNN is made up of layers that are specifically engineered to automatically recognize hierarchical patterns and characteristics in images. It is inspired by the human visual system. Convolutional layers are used to apply filters to input images to capture spatial relationships and localized information. Pooling layers improve computational efficiency, lessen overfitting, and decrease dimensionality while preserving important information. Fully linked layers are a common endpoint of CNNs, allowing for advanced feature extraction and categorization. CNNs have shown to be incredibly successful at tasks like object identification, picture classification, and segmentation because of their capacity to learn complex patterns. This has revolutionized several fields that depend on the analysis and interpretation of visual data.

**Algorithm for Convolutional Neural Network(CNN)**

Step 1: Importing & Setting Up Libraries

Step 2: Preprocessing and dataset handling

Step 3: Execute Model Architecture

Step 4: Carry Out Model Training

Step 5: Carry Out Model Assessment

Step 6: Determine the validation set's accuracy and loss and print the results.

**Statistical Analysis**

The SPSS software is employed to conduct statistical analysis of Novel Feedforward Neural Networks and Convolutional Neural Networks, with independent variables comprising image, objects, distance, frequency, modulation, amplitude, volume, and decibels[(Wang et al. 2023)](https://paperpile.com/c/S6cZKE/gvoV). The dependent variables encompass objects and images. An independent T-test analysis is performed to assess the accuracy of both methodologies.

**Results**

In comparison to the Convolutional Neural Network, the FNN algorithm performs more effectively in forest fire detection from a dataset.

**Table 1.** Improved accuracy for predicting Accuracy of Forest fire Detection using FNN(93.4%) compared with CNN(87%)

**Table 2.** The mean and standard deviation of the group and the accuracy of the FNN and CNN were 93.4% and 1.35, 87% and 1.17 respectively.

**Table 3.** Involves the independent sample test that revealed a substantial variation in accuracy among the suggested two stages and the standard single stage. Since p<0.05, there is a substantial variation between the two methods.

**Figure 1.** Represents the accuracy and mean accuracy calculation of the conventional method and the proposed over-selected input. The proposed method attained a mean accuracy of 93.4%.

**Discussion**

We investigated the efficiency of a novel feedforward neural network (FNN) vs a convolutional neural network (CNN) for the detection of forest fires. The results showed that the FNN was more accurate than the CNN. Because of its specific architecture, the FNN was able to capture complex data patterns, which is very important when trying to identify subtle aspects in images. This helped to explain why its accuracy was higher than that of the CNN model. Our FNN model outperformed the industry standards when compared to earlier studies, providing more dependable and versatile detection skills at different environmental conditions and scales. Nevertheless, issues like processing complexity and the requirement for additional improvement in the detection of tiny flames still exist. Essentially, the ability of our FNN to identify forest fires accurately marks a major achievement in this field, indicating the possibility of more flexible and effective fire monitoring systems for the protection of forests.

The results of our comparison between a novel feedforward neural network (FNN) and a convolutional neural network (CNN) for the detection of forest fires were greatly impacted by variables such as dataset quality, size, and diversity. Because it was designed for complex pattern identification, the FNN fared better than the CNN because it could identify minute details in images. For real-time applications, computational complexity is a barrier that requires additional optimization. Enhancing adaptability in identifying changing fire patterns and environmental changes and future directions involves merging multi-model data sources and continuous model updates, which should result in more reliable forest fire detection systems.

**Conclusion**

Promising findings came from our comparison of a novel feedforward neural network (FNN) with a convolutional neural network (CNN) for the detection of forest fires. With an accuracy of 93.4%, the FNN outperformed the CNN with 87%. This notable performance difference highlights how well the FNN detects forest fires because of its customized architecture, which is excellent at identifying complex patterns in pictures. Although both models demonstrated proficiency, the FNN's increased accuracy suggests that it may be a more dependable instrument for forest fire detection systems. Nevertheless, real-time implementation still faces computational complexity difficulties, necessitating more optimization. However, these results highlight the FNN's capabilities and motivate it to keep searching for more reliable and accurate forest fire monitoring and prevention technologies.

**DECLARATIONS**

**Conflicts of Interest**

No conflict of interest in this manuscript.

**Author Contribution**

Author Varun M was involved in data collection, data analysis, and manuscript writing. Author S. Kalaiarasi was involved in conceptualization, data validation, and critical reviews of manuscripts.

**Acknowledgment**

The authors would like to express their gratitude towards Saveetha School of Engineering, Saveetha Institute of Medical And Technical Sciences (formerly known as Saveetha University) for providing the necessary infrastructure to carry out this work successfully.

**Funding**

We thank the following organizations for providing financial support that enabled us to complete the study.

1.  Redback Solutions, Vellore

2.  Saveetha School of Engineering.

3.  Saveetha Institute of Medical and Technical Sciences.

**References**

1. [Bhagwat, Tejas, Tobias Kuemmerle, Mahmood Soofi, Paul F. Donald, Norbert Hölzel, Albert Salemgareev, Ingrid Stirnemann, Ruslan Urazaliyev, Matthias Baumann, and Johannes Kamp. 2023. “A Novel, Post-Soviet Fire Disturbance Regime Drives Bird Diversity and Abundance on the Eurasian Steppe.” *Global Change Biology*, November, e17026.](http://paperpile.com/b/S6cZKE/g78AH)
2. [Gorta, Simon B. Z., Corey T. Callaghan, Fabrice Samonte, Mark K. J. Ooi, Thomas Mesaglio, Shawn W. Laffan, and Will K. Cornwell. 2023. “Multi-Taxon Biodiversity Responses to the 2019-2020 Australian Megafires.” *Global Change Biology* 29 (23): 6727–40.](http://paperpile.com/b/S6cZKE/gTDfW)
3. [Hoehler, Matthew S., Artur Chernovsky, Matthew F. Bundy, and Esther Baumann. 2023. “Coherent Laser Ranging of Deforming Objects in Fires at Sub-Millimeter Precision.” *Fire Safety Journal* 140 (October). https://doi.org/](http://paperpile.com/b/S6cZKE/jS2Aj)[10.1016/j.firesaf.2023.103864](http://dx.doi.org/10.1016/j.firesaf.2023.103864)[.](http://paperpile.com/b/S6cZKE/jS2Aj)
4. [Lee, Haebum, and Daniel A. Jaffe. 2023. “Impact of Wildfire Smoke on Ozone Concentrations Using a Generalized Additive Model in Salt Lake City, Utah, USA, 2006-2022.” *Journal of the Air & Waste Management Association*, December, 1–15.](http://paperpile.com/b/S6cZKE/MwA3X)
5. [Lertsinsrubtavee, Adisorn, Thongchai Kanabkaew, and Sunee Raksakietisak. 2023. “Detection of Forest Fires and Pollutant Plume Dispersion Using IoT Air Quality Sensors.” *Environmental Pollution*  338 (December): 122701.](http://paperpile.com/b/S6cZKE/RojhV)
6. [Lindenmayer, David, and Phil Zylstra. 2023. “Identifying and Managing Disturbance-Stimulated Flammability in Woody Ecosystems.” *Biological Reviews of the Cambridge Philosophical Society*, December. https://doi.org/](http://paperpile.com/b/S6cZKE/37fyy)[10.1111/brv.13041](http://dx.doi.org/10.1111/brv.13041)[.](http://paperpile.com/b/S6cZKE/37fyy)
7. [Lin, Kun-Te, Zih-Yang Lin, Cheng-Chieh Huang, Shang-Yan Yu, Jing-Lan Huang, Jian-Houng Lin, and Yan-Ren Lin. 2024. “Prehospital Ultrasound Scanning for Abdominal Free Fluid Detection in Trauma Patients: A Systematic Review and Meta-Analysis.” *BMC Emergency Medicine* 24 (1): 7.](http://paperpile.com/b/S6cZKE/nKs5P)
8. [Saleh, Azlan, Mohd Asyraf Zulkifley, Hazimah Haspi Harun, Francis Gaudreault, Ian Davison, and Martin Spraggon. 2024. “Forest Fire Surveillance Systems: A Review of Deep Learning Methods.” *Heliyon* 10 (1): e23127.](http://paperpile.com/b/S6cZKE/30qir)
9. [Saydirasulovich, Saydirasulov Norkobil, Mukhriddin Mukhiddinov, Oybek Djuraev, Akmalbek Abdusalomov, and Young-Im Cho. 2023. “An Improved Wildfire Smoke Detection Based on YOLOv8 and UAV Images.” *Sensors*  23 (20). https://doi.org/](http://paperpile.com/b/S6cZKE/56pP0)[10.3390/s23208374](http://dx.doi.org/10.3390/s23208374)[.](http://paperpile.com/b/S6cZKE/56pP0)
10. [Wang, Haibin, Hongjuan Ge, Zhihui Zhang, and Zonghao Bu. 2023. “Research on Fire-Detection Algorithm for Airplane Cargo Compartment Based on Typical Characteristic Parameters.” *Sensors*  23 (21). https://doi.org/](http://paperpile.com/b/S6cZKE/gvoV)[10.3390/s23218797](http://dx.doi.org/10.3390/s23218797)[.](http://paperpile.com/b/S6cZKE/gvoV)

**TABLES AND FIGURES**

**Table 1.** Accuracy and significant difference between Feedforward Neural Networks  and Convolutional Neural Networks

|  |  |  |
| --- | --- | --- |
| **S.No** | **GROUPS** | **ACCURACY** |
| **1** | **Feedforward Neural Network** | 91.50 |
| 91.80 |
| 92.40 |
| 92.80 |
| 93.78 |
| 93.80 |
| 94.65 |
| 94.90 |
| 95.60 |
| 93.40 |
| **2** | **Convolutional Neural Network** | 85.60 |
| 85.90 |
| 86.78 |
| 86.90 |
| 87.50 |
| 87.80 |
| 88.50 |
| 88.89 |
| 89.00 |
| 87.80 |

**Table 2.** Group Statistical Analysis of Feedforward Neural Network and Convolutional Neural Network. Mean, Standard Deviation, and Standard Error Mean.

Error Mean is obtained for 10 samples. Feedforward Neural Network has higher mean accuracy and lower mean when compared to Convolutional Neural Network.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Group** | **Algorithm** | **N** | **Mean** | **Std.**  **Deviation** | **Std. Error**  **Mean** |
| **Accuracy** | **1** | FNN | 10 | 93.46 | 1.35 | .427 |
|  | **2** | CNN | 10 | 87.00 | 1.17 | .371 |

**Table 3.** Independent Sample T-test: A Feedforward Neural Network is significantly better than a Convolutional Neural Network with a p-value of 0.000 (p<0.05) for accuracy.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | **F** | **Sig** | **t** | **df** | **Sig.**  **(2-tailed)** | **Mean**  **difference** | **Std. Error Difference** | **Lower** | **Upper** |
| **Accuracy** | Equal variances assumed | .228 | .638 | 10.59 | 18 | .000 | 5.99600 | .56615 | 4.806 | 7.185 |
|  | Equal variances not assumed |  |  | 10.59 | 17.652 | .000 | 5.99600 | .56615 | 4.806 | 7.187 |

**Table 4.** Comparison of the Feedforward Neural Network and Convolutional Neural Network with their accuracy.

|  |  |
| --- | --- |
| **CLASSIFIER** | **ACCURACY(%)** |
| Feedforward Neural Network | 93.4% |
| Convolutional Neural Network | 87.0% |

A blue squares with black text

Description automatically generated

**Fig. 1.** Simple Bar Graph for Comparison of Accuracy. X-axis: FNN Algorithm vs CNN Algorithm Y-axis: Mean accuracy of detection 1SD