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Forest Fire Prediction using Liquid Neural Networks

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Abstract— **Wildfires pose a significant risk to ecosystems, animals, and people. Predicting them early can help prevent major disasters. In this study, a type of neural network called a Liquid Neural Network (LNN) was employed to predict forest fires based on meteorological and climatic data. The LNN model was tested using the Mendeley Forest Fire Dataset, which includes real data such as temperature, humidity, wind speed, and rainfall. With 96% accuracy, the LNN model predicted the probability of a forest fire. These results show that LNNs can be a powerful tool for early forest fire prediction and could help authorities take timely action to reduce damage. Particularly in areas with dry weather and thick vegetation, forest fires represent a significant threat to natural ecosystems, as well as to property and life on Earth. Early detection and prediction of such fires are crucial for effective disaster management and mitigation efforts. This research explores the use of LNNs, a dynamic and flexible type of neural model, to predict forest fires based on meteorological and climatic data. The model was trained and tested on the Mendeley Forest Fire Dataset, which includes various features such as heat, relative humidity, breeze velocity, and precipitation—factors known to influence fire occurrences. Unlike traditional models, LNNs can adapt more efficiently to changing input patterns, making them well-suited for handling time-sensitive and non-linear data. LNN achieved a prediction accuracy of 96%, resulting in good efficacy in identifying conditions that may lead to forest fires. This level of performance demonstrates the potential of LNNs to support real-time decision-making tools for forest management and emergency response planning.**

Keywords—Forest Fire, Neural Network, Natural Calamities, Adaptive Systems, Spatiotemporal Modeling.

I. Introduction

LNNs are a type of Recurrent Neural Network (RNN) designed to handle data that changes over time. LNNs are especially useful for making predictions based on dynamic or time-dependent information, such as weather patterns and environmental conditions. Forest fires are influenced by many changing factors like temperature, wind speed, humidity, and rainfall. LNNs can learn the complex, non-linear relationships between these variables, helping the model understand how they interact to increase or decrease the risk of fire. Unlike traditional models, LNNs are more flexible and can adapt as new patterns appear in the data. This is important because environmental conditions change constantly, and a model that can adjust to these changes improves prediction accuracy. Weather and environmental data are collected over time. LNNs are naturally suited to work with this type of sequential data. They can track how conditions evolve over hours, days, or weeks and use this information to forecast fire risk more precisely.

Due to their efficiency and adaptability, LNNs can be used in real-time systems. This allows forest management teams to receive timely alerts and take early action when the risk of fire becomes high. LNNs can be used as a reliable tool for early warning systems, reducing the damage caused by uncontrolled forest fires. Traditional models often treat data as static, meaning they don't fully account for how conditions change over time. LNNs, however, are built to process time-series data, such as hourly temperature or wind changes. This allows LNNs to learn patterns over time and make better predictions based on recent trends.

Forest fire risk depends on many interacting factors like weather, vegetation, and terrain. LNNs can model these complex and non-linear relationships better than traditional statistical or rule-based models. LNNs can adapt to new or unexpected data patterns better than fixed traditional models. For example, if weather conditions shift due to climate change, LNNs are more capable of adjusting their predictions accordingly, making them more reliable in changing environments. Compared to some Deep Learning (DL) models [1] that need massive datasets, LNNs are relatively lightweight and efficient. This makes LNNs suitable even when data is limited or collected in remote forest areas. LNNs are designed to make fast, real-time decisions. This is critical in forest fire management, where early warnings can help prevent fires from spreading and allow quicker responses from firefighting teams. LNNs have a simpler internal structure that naturally avoids overfitting to training data, which is a common problem in complex traditional neural networks. This makes their predictions more general and reliable in real-world scenarios.

II. RELATED WORKS

Many traditional models, such as Logistic Regression or basic decision trees, and Support Vector Machines (SVMs), treat input data as static data. However, environmental conditions like temperature, humidity, and wind speed change over time. Ignoring this time-dependent nature leads to inaccurate predictions. Forest fires result from a combination of many factors [2]. Traditional models like Contrastive Vision Transformer(CviT), and eXtreme Gradient Boost (XGB) often cannot capture the complex, non-linear relationships between these variables. As a result, traditional methods oversimplify the problem and miss subtle patterns that could signal an approaching fire. Some existing systems are slow and not optimized for real-time use. Traditional methods [3] require all input data to be pre-collected and processed in batches, which delays prediction and response, especially in emergencies.

Traditional Machine Learning (ML) models [4] may either learn too much from the training data (overfitting) or fail to learn enough (underfitting). Both issues reduce prediction performance when new or unseen data is introduced. Many existing models work well only in the regions they were trained on. Traditional methods struggle to adapt to different environments, such as forests with varying terrain, climate, or vegetation types. Traditional methods always fail in accurately predicting forest fires due to overlooking correlations between multiple factors like wind, speed, and vegetation type, considering a narrow set of variables like weather data, historical fire data, and vegetation types, and ignoring real-time satellite imagery and real-time data feeds. Due to these limitations, many existing models fall short of predicting forest fires accurately and quickly. This makes it harder for authorities to take timely action, increasing the risk of damage to forests, wildlife, and human settlements. A review of existing forest fire prediction models is shown in Table I. The review includes the method employed, the dataset used, the performance analysis, and direct technical demerits from existing works.

TABLE I. A REVIEW OF EXISTING FOREST FIRE PREDICTION TECHNIQUES

Research	Method	Dataset	Performance Analysis	Direct Technical Demerit from Existing Works
[5]	Stacking model, random sampling	Hotspot data collected from Chongqing City, China	Accuracy=94.47%	The model does not learn from how environmental variables change over time. The model is not efficient in capturing time-dependent patterns in the data.
[6]	SVM	Public dataset	Accuracy=87%	Low accuracy. It is not inherently designed for time-series data. It still operates on static input features.
[7]	CViT-Pool Former	Forest Fire Big Data dataset	Accuracy= 92.8%	The model does not explicitly capture how environmental and weather conditions evolve. The model is not designed to learn temporal dependencies. Heavy Preprocessing Requirements, Computational Complexity.
[8]	Wireless Sensor Network (WSN)	Public dataset	Accuracy= 86.67%	Limited Predictive Power and Generalization. A prediction accuracy of 86.67%, while useful, is relatively low compared to more advanced models that can reach above 90–95% using richer temporal and spatial modeling techniques.
[9]	Convolution Neural Network (CNN) + transformer + Blockchain	Public Dataset	Accuracy=91%	Lack of real-time temporal modeling and scalability challenges in drone and blockchain integration, Lack of Explicit Time-Series Analysis, Latency, and Overhead from Blockchain Integration.
[10]	Back Propagation Neural Network	Real-time dataset	Accuracy=90%	Training on Simulated Data (FlamMap) Only, No Real-Time Temporal Modeling
[11]	ML	Amazon Rainforest fires	Accuracy=89%	Low accuracy.
[12]	Multi-Sensor Network system	Real-time dataset	Accuracy=93.6%	The approach relies heavily on the widespread deployment of physical sensors. Sensor failure or damage results in false predictions. The system's performance relies on accurate readings from multiple sensors, but real-world sensor data can be noisy, delayed, or inaccurate, especially in changing field conditions.
[13]	XGB	Self-built dataset. Data was collected from Alberta, Canada.	Accuracy=87.2% Sensitivity=75%	It is a non-sequential model that does not natively capture temporal dependencies. Low accuracy. A sensitivity of 75% indicates that one in four actual fires might not be detected.
[14]	Federated Learning, IoT-Based Forest Fire Prediction	Public Dataset	Accuracy=76%	Low accuracy, Severe Class Imbalance.

III. Proposed Methodology

A. Dataset details

Mendeley Forest Fire Dataset [15], a curated dataset comprising images for forest fire detection and classification, was employed in this research. The dataset contains 2,974 images categorized into fire and non-fire classes. The Mendeley Forest Fire Dataset is a well-known dataset commonly used for forest fire prediction. The dataset contains meteorological and fire occurrence data collected from a forested region in Portugal. It is primarily used to predict the area burned by forest fires based on weather conditions and time features. The dataset details are shown in Table II.

TABLE II. DATASET DETAILS

Feature name	Description
Temperature (°C)	Measures the surrounding air temperature at the time of the fire record.
Relative Humidity (%)	Shows how much moisture is present in the air compared to the maximum possible.
Wind Speed (km/h)	Indicates the speed of wind, which can influence fire spread.
Rainfall (mm)	Records the amount of rain during the period, which can reduce fire chances.
Fine Fuel Moisture Code (FFMC)	Estimates the moisture content in smaller vegetation that ignites quickly.
Duff Moisture Code (DMC)	Represents the dryness level in loosely packed forest floor materials.
Drought Code (DC)	Captures long-term dryness and deep fuel layer conditions.
Initial Spread Index (ISI)	Predicts how quickly a fire might spread when started.
Build-Up Index (BUI)	Measures fuel availability and build-up potential.
Fire Weather Index (FWI)	Provides a comprehensive measure of fire risk based on other indices.
Classes (Binary)	Label whether a fire occurred (1) or not (0) for that record.

B. Preprocessing

One-hot encoding was used for categorical encoding. Z-score normalization was used to normalize numerical inputs. Binary transformation was used to handle skewed targets. Class weighting was used to avoid bias to the majority class. Area clipping was used for outlier removal. Pseudo-sequence formatting was used to suit LNN's time-based architecture. Stratified sampling was used for splitting the training and testing data.

C. Construction of LNN

The input layer is used to accept forest fire features over time. The input layer accepts sequential environmental data inputs (e.g., temperature, humidity, wind speed, rainfall). The liquid cell is used to model dynamic time-varying processes. The liquid cell is the core of the LNN, modeled by differential equations that update the hidden state over time. The readout layer is used to map the internal state to the probability of fire occurrence. The readout layer takes the final hidden state and produces a prediction probability. Optimizer is used to train the network using temporal gradient descent. The optimizer trains the network using gradient-based methods like Adam. The construction of LNN is shown in Fig.1.

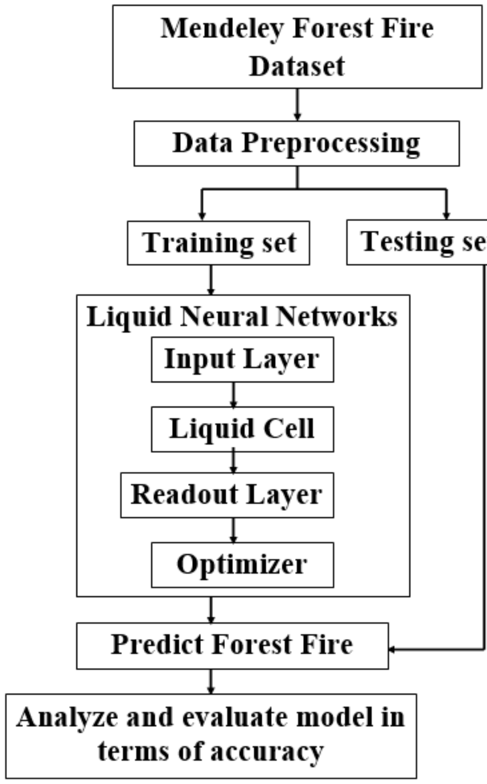

Fig. 1. Construction of LNN

The algorithm for training the LNN model is given below:
For each training instance with sequence $\{x_1, x_2, ..., x_T\}$:

Calculate $h_t = \int_{t=1}^{T} f(Wx_t + Uh_{t-1} + Vx_{t-1})$ with $x_0 = 0$, $h_0 = 0$.

Where x_t indicates input vector at time step t, h_t indicates hidden state at time t, $f(.)$ indicates activation function, T represents sequence length, and t represents timestep.
Where W, U, and V represent weight matrices.
At the final time step:

Calculate Predicted label: $y_p = \sigma(w_{out}^T\ h_T)$, where y is the target label.

Where σ is the sigmoid activation for binary classification, and w_{out} indicates the output weight vector.

The algorithm for testing the LNN model is given below:
For each Test instance:

Calculate predicted class $y_{class} = \begin{cases} 1, & y_p \geq 0.5 \\ 0, & otherwise \end{cases}$

Compute accuracy $A = \frac{1}{N}\sum_{i=1}^{N} I_f\ (y_i^{class} = y_i)$

Where I_f indicates the indicator function, N represents the total number of test samples, and y_i indicates the actual target value.

IV. Results and Discussion

A. Experimental Setup

The Linux operating system, Jupyter Notebook, Python 3.8, Intel i7, 16GB RAM, 50 GB SSD Storage, and PyTorch were used as software and hardware resources for the experimental part. The configuration of LNN is shown in Table III.

TABLE III. LNN MODEL CONFIGURATION

Parameter	Value
Input dimension	10 features
Hidden state size	64
Activation Function	sigmoid
optimizer	Adam with an initial learning rate of 0.001
epochs	30
Batch size	64
Output layer	Single neuron with sigmoid activation

B. Comparative Analysis

From Table IV, it's clear that the LNN model achieved the highest prediction accuracy of 96% compared to the other existing methods. While CViT, Multi-Sensor systems, and Stacking models also showed strong performance, LNN outperformed them all. This shows that LNN is more effective at learning complex patterns in environmental data, making it a better choice for accurate and early forest fire prediction. The graphical interpretation is also shown in Fig. 2.

TABLE IV. ACCURACY COMPARISON: LNN VERSUS EXISTING APPROACHES

Method	Accuracy
CViT [7]	92%
Multi-Sensor Network System [12]	93%
Stacking Model [5]	94%
LNN (Proposed)	96%

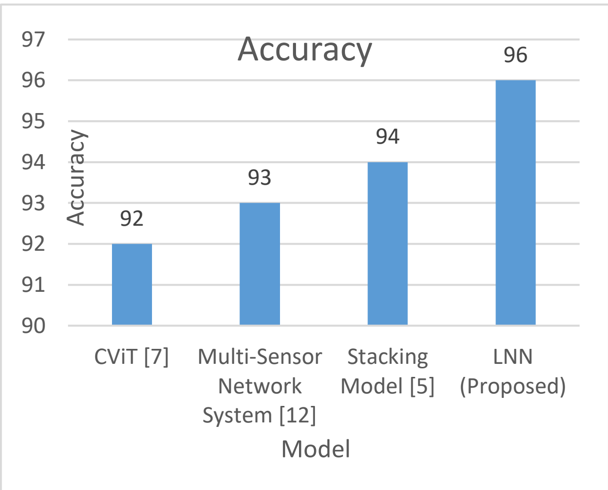

Fig. 2. Accuracy Comparison Graph

V. Conclusion and Future Scope

This research focused on predicting forest fires using a special kind of neural network called an LNN. Unlike traditional models, the LNN can understand how environmental conditions like temperature, humidity, wind speed, and rainfall change over time. This helps the model make smarter and more accurate predictions. The model was trained and tested using the Mendeley Forest Fire Dataset, which contains real-world weather and fire-related data. After applying the necessary preprocessing steps and training the LNN, the model was able to reach a prediction accuracy of 96%. This means that in most cases, the model correctly identified whether a fire would occur or not. Such a high accuracy shows that the LNN is highly effective in spotting early signs of forest fires. This can help authorities respond quickly, reduce damage to nature, protect wildlife, and keep nearby people safe. The outcome of this research proves that LNNs are a reliable tool for forest fire prediction and can play an important role in disaster prevention and forest safety. In the future, this model can be connected with live sensor networks in forests to give real-time fire warnings and help with faster emergency responses.

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