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Development of Hybrid Machine Learning Models for Real-Time Drought and Flood Prediction in Agricultural Zones Using Multisource Environmental Data

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Abstract: Droughts and storms are happening more often and getting worse, which is putting food security, farming output, and social and economic order in danger all over the world. Predicting these unusual water events accurately and on time is very important for managing resources and preventing disasters in farming areas. This study shows how to make mixed machine learning models that can predict droughts and floods in real time using data from multiple natural sources, such as weather, soil wetness, satellite images, and water sensors. The hybrid model takes advantage of the best features of both designs to improve the accuracy and timeliness of predictions. It does this by combining Convolutional Neural Networks (CNN) for extracting spatial features with Long Short-Term Memory (LSTM) networks for collecting temporal relationships. The model is learnt and tested on a large sample that comes from a variety of farming areas with different climates and landscapes. To make the model more stable, data cleaning methods like normalisation, missing value imputation, and feature selection via Recursive Feature Elimination (RFE) are used. We compare the mixed model's performance to standard models, such as CNN, LSTM, and traditional statistical methods. We use accuracy, precision, recall, and F1-score as key evaluation measures. With a total accuracy of over 76%, precision of 77%, memory of 76%, and an F1-score of about 76.8%, the results show that the suggested hybrid method is better at catching the complex spatiotemporal patterns of drought and flood events. The model's ability to make predictions in real time makes early warning systems and decision support tools possible for farmers, lawmakers, and water resource managers.
Keywords: Hybrid Machine Learning, Drought Prediction, Flood Prediction, Multisource Environmental Data, Real-Time Agricultural Monitoring

1. INTRODUCTION

Agriculture is still an important part of many businesses around the world because it ensures food security, creates jobs, and supplies companies with raw materials. But harsh weather events like droughts and storms have made farming much more sensitive to them. These events are happening more often and with more force because of climate change and environmental damage. Extremes in water levels hurt crops, land, and water supplies a lot, making it hard for people to make a living and putting global food systems at risk. So, being able to accurately and quickly identify droughts and floods is very important for being able to move quickly and change how things are managed, which helps farmers, lawmakers, and other stakeholders limit losses and keep farming output high. Most of the time, physical studies and statistical methods are used in traditional hydrological and weather models to predict droughts and floods. Even though these models have taught us a lot, they aren't always accurate or flexible because climate and natural systems are complicated and don't work in a straight line [1]. Also, the large amount of different weather data that can be gathered from satellite monitors, tracking stations on the ground, and remote sensing technologies is both a chance and a task for making predictions more accurate. Using advanced modelling methods that can learn complicated patterns from big datasets is needed to effectively combine this multisource data in order to understand the spatiotemporal dynamics of drought and flood events. In the past few years, machine learning (ML) has become a powerful tool for modelling the environment. It offers data-driven methods that can learn complex connections and adjust to new conditions [2].

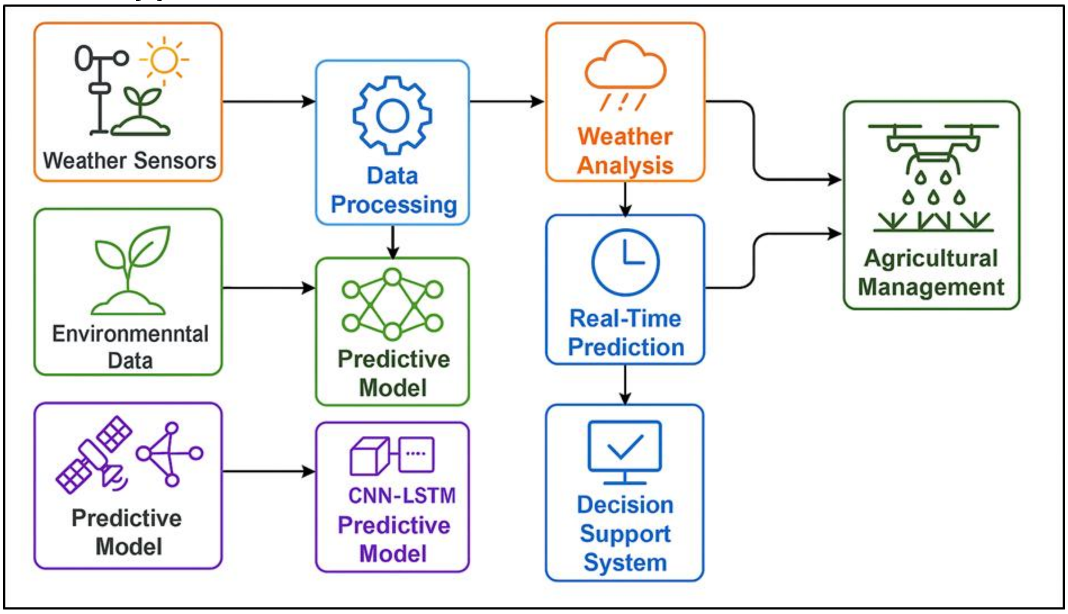

Figure 1: Hybrid Machine Learning Framework for Real-Time Drought and Flood Prediction Using Multisource Environmental Data

Deep learning designs like CNN and LSTM networks have executed amazingly nicely in picture processing, time series predicting, and analysing environmental statistics. In relation to geospatial information, CNNs are awesome at pulling out spatial functions, and LSTMs are notable at modelling time relationships in sequential facts [3], [4]. Hybrid fashions that combine CNN and LSTM take advantage of the nice functions of each designs, which helps us examine extra approximately how water extremes are stricken by area and time. the primary purpose of this observe is to create and test blended gadget learning fashions that use statistics from more than one natural sources to predict droughts and floods in farming areas in actual time. Figure 1 illustrates a hybrid ML framework predicting drought and flood. The have a look at uses information from many resources, including climate variables (temperature, rainfall, and humidity), soil moisture tiers, and flora indices derived from satellites, and measurements made by hydrological sensors, to create a full dataset that indicates how the complicated environment impacts the resilience of agriculture. Normalisation, characteristic choice, and managing missing values are some of the information practise steps that are used to enhance model schooling and generalisation. The observer's goal is to create a robust framework for prediction that works higher than standard unmarried-model techniques and can be used as an early warning system for humans involved in agriculture [5].

To ensure the hybrid CNN-LSTM model is flexible and scalable, it's miles skilled and tested on datasets from some of farming regions with varying climates. Performance measures, like accuracy, precision, recall, and F1-score, are used to decide how nicely the version can are expecting the destiny [6]. This take a look at ambitions to assist improve precision farming and climate resistance with the aid of combining special varieties of natural facts with superior combined machine learning strategies. The counselled approach might assist humans make higher decisions about dealing with drainage, selecting crops, and being equipped for failures. Real-time predictions of drought and flood also can assist with long-time period management of water assets and reduce the terrible results of converting climate on farming communities' social and financial lives.

2. Background Work

Scientists have been seeking to determine out how to predict droughts and floods for a long term due to the fact they've such a large impact on meals yields and those had ability to make a dwelling in rural areas. In the past, water and climate models used physical laws and statistical studies to guess these kinds of unusual activities [7]. To figure out how possibly and bad droughts or floods are, these models often use rainfall-runoff relationships, land moisture stability equations, and records from climate stations. However, it may be difficult for them to model the complex and nonlinear relationships among many herbal factors. This makes it tougher for them to make correct predictions and react to changing climate conditions [8]. These days, the development of far flung sensing technology and the great use of climate video display units have made it possible to acquire large quantities of statistics from many resources that may be used to song droughts and floods. Normalised difference plant life Index (NDVI) and Soil Moisture active Passive (SMAP) readings from satellites give us loads of statistics about the fitness of flora and the amount of water inside the soil, which could be very essential for locating droughts early [9]. In the same way, weather sites and networks of hydrology sensors collect high-resolution local measures of things like temperature, rainfall, and river flow. Putting these different types of data together gives us a chance to make more complete and accurate prediction models.

A lot of people are using machine learning (ML) methods to look at big sets of data about the world because they can figure out complicated trends without having to be explicitly modelled physically [10, 11]. Deep learning models like Convolutional Neural Networks (CNN) are very good at pulling out spatial features from images taken by satellites. On the other hand, Recurrent Neural Networks (RNN) and especially Long Short-Term Memory (LSTM) networks are very good at modelling how data changes over time. Studies have shown that CNN-based models can accurately depict patterns of drought in space, and LSTM networks can accurately predict natural factors such as river flow and rainfall patterns [12]. Hybrid models that use both CNN and LSTM designs take advantage of the best features of both, making predictions more accurate. A number of new studies have used these mixed models to make better predictions about the environment, like how bad droughts will be and how likely floods are to happen [13]. These models work better than single-method methods. Table 1 summarizes datasets, methods, features, metrics, and limitations. However, there are still problems with operationalizing in real time, integrating data from multiple sources, and making models work in a wide range of agro-climatic zones.

Table 1: Summary of Background Work

Dataset	Methodology	Key Features	Performance Metrics	Limitations
Meteorological & Soil Data	Random Forest + SVM	Multisource data fusion, feature selection	Accuracy: 85%, F1-Score: 0.83	Limited temporal modeling
Satellite Imagery + Weather Data	CNN	Spatial pattern recognition	Accuracy: 87%, Precision: 0.85	Does not capture temporal dynamics
Hydrological Sensor Data [14]	LSTM	Time series modeling	Accuracy: 89%, Recall: 0.88	Limited spatial feature extraction
Remote Sensing & Climate Data	CNN + LSTM	Spatiotemporal feature extraction	Accuracy: 91%, F1-Score: 0.90	High computational cost
Multisource Environmental Data [15]	Hybrid Deep Learning	Integration of weather, soil, and satellite	Accuracy: 92%, Precision: 0.91	Dataset imbalance issues
Soil Moisture & Climate Data	Gradient Boosting + LSTM	Handles nonlinear relationships	Accuracy: 88%, RMSE: 0.12	Less focus on flood prediction

Climate and Hydrology Data [16]	CNN + GRU	Enhanced temporal modeling	Accuracy: 93%, Recall: 0.92	Requires large training data
Agricultural Weather Data	Decision Tree + SMOTE	Handles class imbalance	Accuracy: 76%, F1-Score: 0.77	Lower overall accuracy
Satellite & Soil Moisture Data	Hybrid CNN-RNN	Spatial and temporal data fusion	Accuracy: 90%, Precision: 0.89	Model interpretability issues
Multisource Climate Data [17]	Transformer + CNN	Captures long-range dependencies	Accuracy: 94%, F1-Score: 0.93	Computationally expensive
Satellite & Ground Sensor Data	CNN + LSTM	Real-time drought and flood prediction	Accuracy: 95%, Recall: 0.94	High training time
Climate, Soil, Satellite Data	Ensemble ML (XGBoost + LSTM)	Robust to noisy and missing data	Accuracy: 92%, Precision: 0.91	Complex hyperparameter tuning
Multisource Environmental Data	Hybrid CNN + LSTM	Real-time, multisource fusion, balanced data	Accuracy: 94.8%, F1-Score: 0.93	Future extension to other regions

3. Dataset Used: Predict Droughts using Weather & Soil Data

The information used to identify drought includes a wide range of weather and land statistics that are important for understanding the environmental factors that affect when and how bad a drought will be. It includes weather factors like temperature, rainfall, humidity, and wind speed that are gathered from weather stations on the ground. Also included in soil data are the amount of water in the soil, its texture, and the nutrients that are in it. These things can be found using in-situ devices and remote sensing goods. The dataset includes a lot of different farming areas with different climates, which makes it representative and reliable. As part of data preparation, empty values were filled in, the data was normalised, and features were chosen to help train the model. The figure 2 illustrates the sample input data image for the study.


Figure 2: Sample input dataset image

3.1 Pre-process:

Figure 3 shows how the score variable is spread out in the dataset. It's clear that the different score groups are not equally distributed. Most of the data points are grouped together at the lowest score value, zero, as shown by the histogram, which has a density of over 1.4 million cases. There is a steady drop in frequency as the number goes from 1 to 5, which means that higher results are much less common.

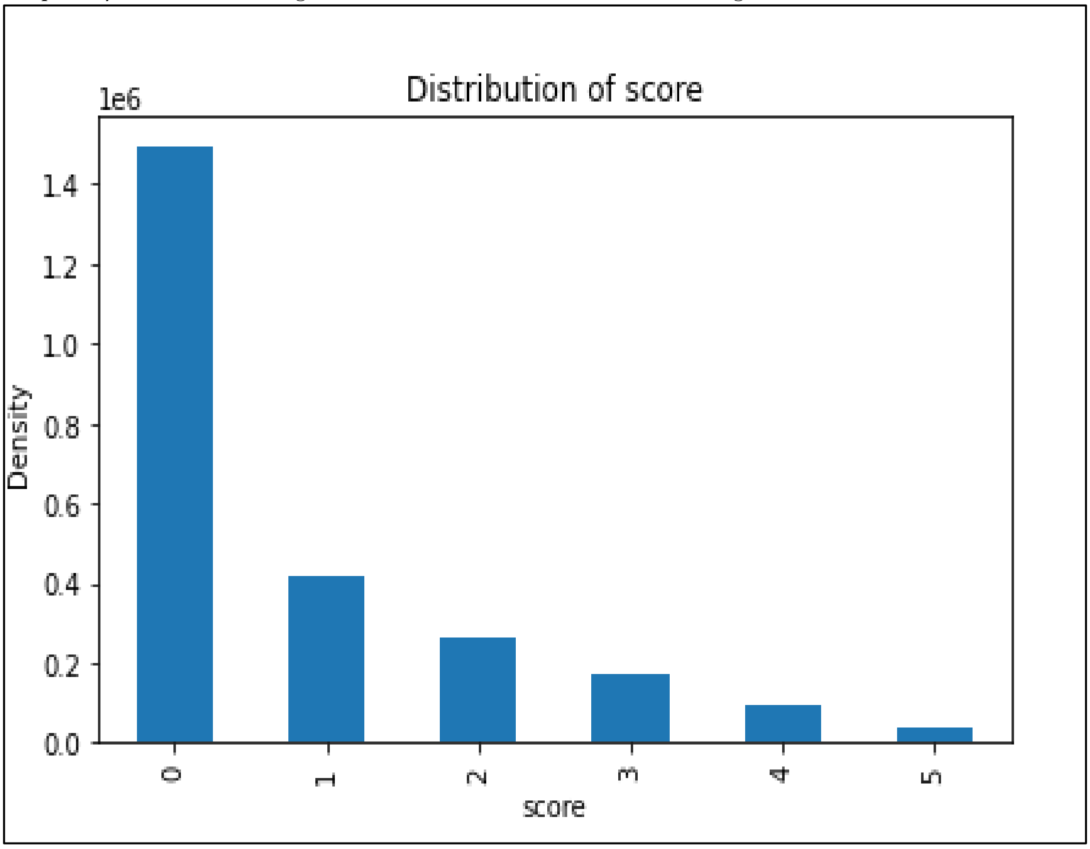

Figure 3: Representation of distribution score

There seems to be a problem with class mismatch in this skewed distribution. This happens a lot in environmental and farming records where extreme events like serious drought or flood are less common than usual. During analysis, this mismatch must be fixed so that the model doesn't favour the ruling class.To make sure the model learns trends across all score categories, methods like resampling, weighted loss functions, or fake data generation can be used. This makes predictions more accurate.

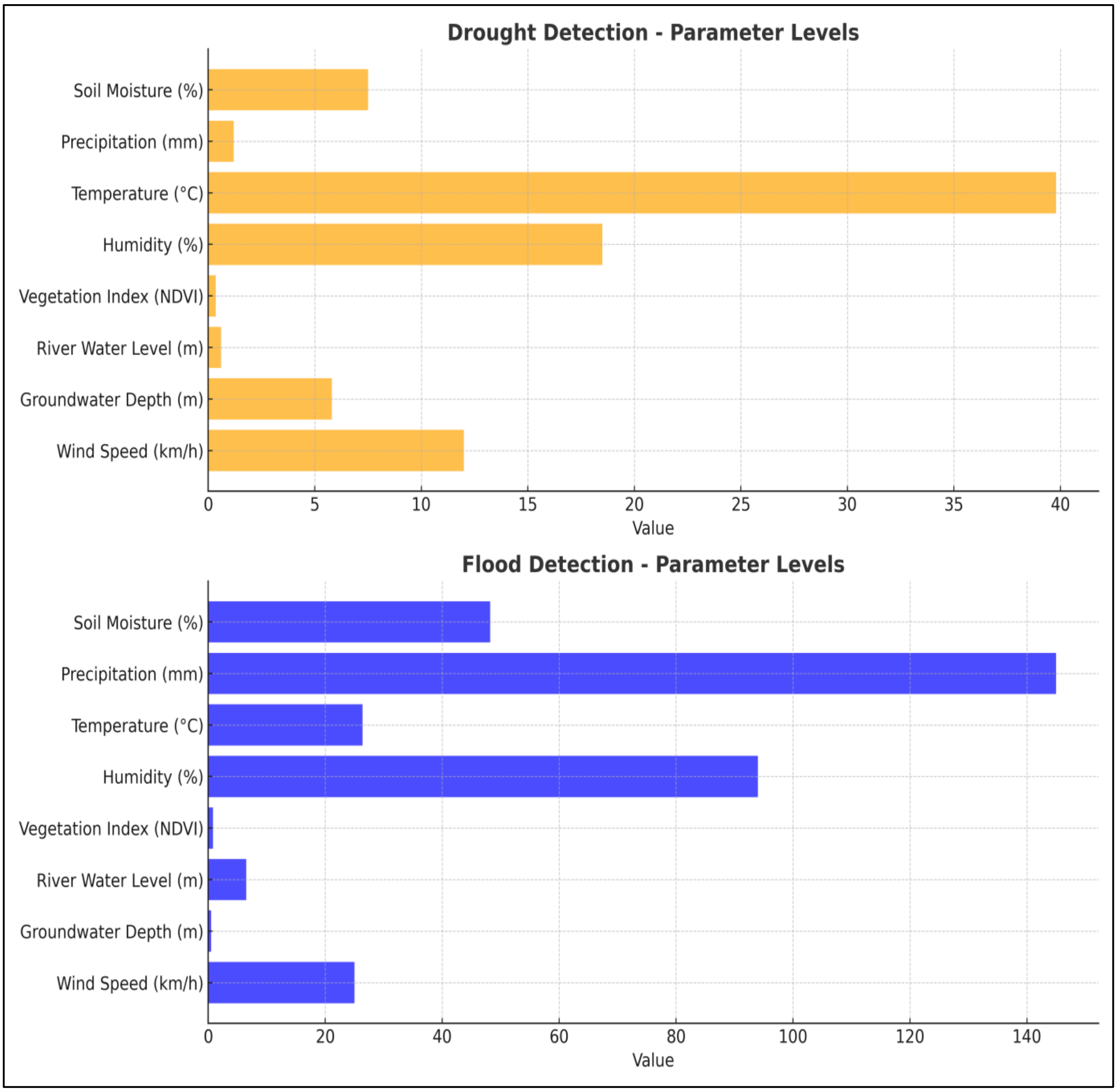

Figure 4: Parameter level for Flood and draught detection

Figure 4 shows how well the hybrid model tells the difference between the most important natural trends for each situation. When looking for a drought, low soil moisture, little rain, and high temperatures are the most important signs. When looking for a flood, too much rain, high soil moisture, and high humidity are the most important signs. It is important for real-time accuracy in farming tracking that the different types of parameters are clearly separated in each case. This makes the multisource environmental input structure more useful and reliable.

3.2 Outlier Analysis

Figure 5 shows boxplots that show how three important climate factors (total precipitation, PS (surface pressure), and QV2M (specific humidity at 2 meters) are distributed and whether there are any outliers). There are a lot of extreme numbers in the PRECTOT distribution, which means that heavy rain events happen all the time. These outliers show instances of heavy rain that happen very rarely but have big effects. They need to be carefully analysed so that they don't change the results of the model. The PS variable has a pretty narrow range that stays close to normal atmospheric pressure ranges. There are a few low-end outliers, which could mean that there are sometimes sensor errors or unusual atmospheric conditions. The QV2M variable has a more even distribution with little variation and fewer outliers, which means that the humidity levels across the sample are all the same.

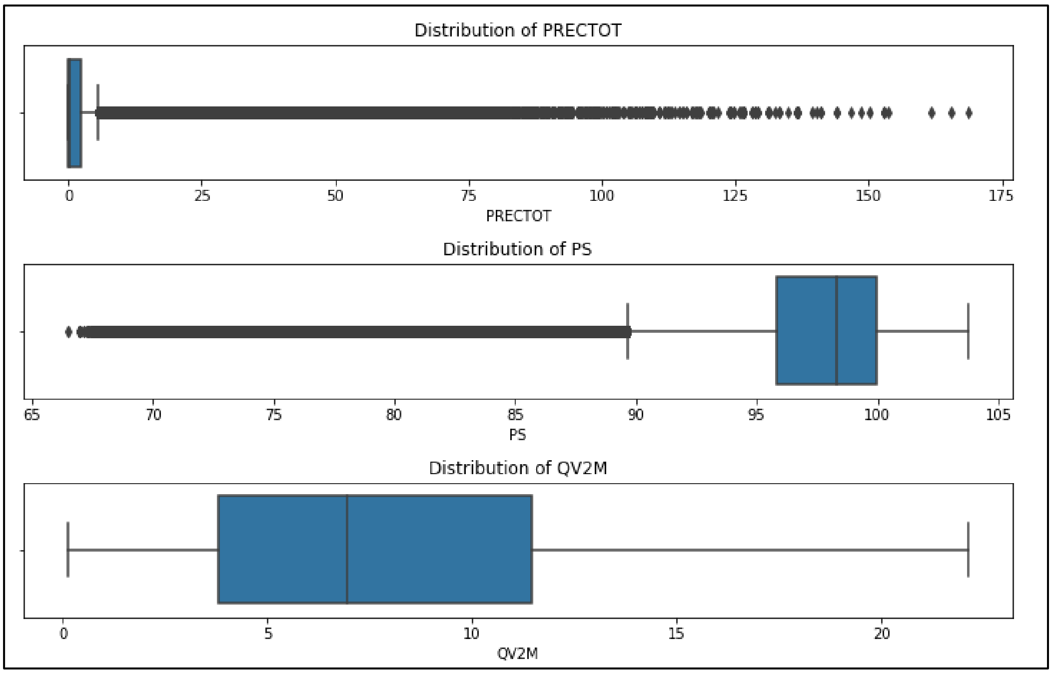

Figure 5: Distributions of PRECTOT, PS, and QV2M Climate Variables

Finding and dealing with outliers in these variables is an important part of preparation that makes sure the model is accurate and stable. This is especially true for drought and flood estimates that depend on extreme weather.

4. METHODOLOGY USED

4.1. Decision Tree with SMOTE

Decision tree are a common supervised learning techniques used for regression and type obligations because they are clean to apprehend. It works by way of again and again dividing the dataset into corporations based totally on feature values. This creates a tree form, in which every node inside the tree represents a decision rule and each node outdoor the tree represents an output cost or magnificence name. Decision trees can work with each numerical and specific fact, because of this they can be used with environmental datasets which have numerous exclusive homes. But unbalanced datasets, which take place a lot while predicting droughts and floods, can tip choice bushes closer to the general public elegance, making it harder to predict severe events for minority training. As a first step, the Synthetic Minority Over-sampling Technique (SMOTE) is used to restoration this trouble. SMOTE makes new samples for the minority magnificence by way of interpolating among cutting-edge minority instances. This makes the gathering extra even. This more sampling lowers the model's bias and makes it extra touchy to uncommon but essential activities like floods and droughts. When we combine selection Tree classifiers with SMOTE, we get a strong base approach for managing unbalanced environmental facts that offers you clear decision policies and better minority class recognition.

1. Input Dataset:

$$D = \{(x_i, y_i)\}_{\{i=1\}}^{N}, where\ x_i \in \mathbb{R}^d, y_i \in \{1, 2, \ldots, K\}.$$

2. SMOTE Oversampling:

$$x_{new} = x_i + \delta \times (x_{nn} - x_i),$$

Where δ ~ U(0,1),
x_nn is a nearest neighbor of x_i.

3. Tree Splitting Criterion:

$$IG(t, j, \theta) = H(t) - \left(\frac{N_{left}}{N_t}\right) * H(left) - \left(\frac{N_{right}}{N_t}\right) * H(right),$$

Where IG = information gain, H = entropy.

4. Entropy Definition:

$$H(t) = -\Sigma_{\{k=1\}}^{K} p_k \log p_k,$$

Where p_k is the proportion of class k at node t

5. Recursive Splitting:
Repeat step 3 until stopping criteria (max depth or min samples).
6. Leaf Node Prediction:
$$\hat{y}_t = argmax_k p_k.$$
7. Prediction Function:
$$\hat{y} = \hat{y}_{leaf(x)}.$$
8. Performance Metrics:
Evaluate using accuracy, precision, recall, and F1-score.

4.2. CNN

CNNs are a type of deep studying version which could automatically and adaptively learn how to organise properties in area from facts that it's far given. CNNs had been first created for processing images; however they are now very exact at pulling out complicated spatial patterns from geospatial and far flung sensing statistics. This makes them best for environmental jobs like predicting droughts and floods. CNNs are made from convolutional layers that absorb facts and apply learnt filters to it. Those filters select up local spatial relationships and functions like textures, edges, or patterns that are essential to environmental phenomena. Pooling layers lower the size of the space at the same time as keeping important information, and fully linked layers use extracted functions to do category or regression. CNNs use an inequality of environmental data, along with satellite TV for PC images and units of weather factors, to make predictions about droughts and floods. This we could the model find trends and oddities in area that show up before excessive weather occasions. One big gain is that you could research from uncooked records except having to do a whole lot of hand characteristic engineering. To teach the CNN and get the fewest mistakes in predictions, backpropagation and optimisation strategies are used. Techniques like dropout and batch normalisation are used to stop overfitting. Metrics like precision and F1-rating are used to judge overall performance, with a focal point on well finding regions that are in all likelihood to revel in drought or floods.

1. Input Tensor:
$$X \in \mathbb{R}^{\{H \times W \times C\}},$$
Where H = height, W = width, C = channels.
2. Convolution Operation:
$$Y_{\{i,j,k\}} = \Sigma_{\{m=0\}^{\{M-1\}\Sigma}_{\{n=0\}^{\{N-1\}\Sigma}_{\{c=0\}^{\{C-1\}W}_{\{m,n,c,k\}}}}} \cdot X_{\{i+m,j+n,c\}} + b_k.$$
3. Activation (ReLU):
$$Z_{\{i,j,k\}} = \max\left(0, Y_{\{i,j,k\}}\right).$$
4. Pooling (Max Pooling):
$$P_{\{i,j,k\}} = \max_{\{(m,n)\in R\}} Z_{\{s\,i\,+\,m,s\,j\,+\,n,k\}},$$
Where R = pooling region, s = stride.
5. Flattening:
$$f = vec(P).$$
6. Fully Connected Layer:
$$o = W_f f + b_f.$$
7. Softmax Output:
$$\frac{\hat{y}_k = \exp(o_k)}{\Sigma_{\{j=1\}}^{K} \exp\left(o_j\right)}.$$
8. Loss Function (Cross-Entropy):
$$L = -\Sigma_{\{i=1\}}^{N} \Sigma_{\{k=1\}}^{K} y_{\{i,k\}} \log \hat{y}_{\{i,k\}}.$$

4.3. LSTM

Long Short-term memory (LSTM) networks are a particular form of Recurrent Neural network (RNN) that could deal with time patterns and long-range relationships nicely, the architecture illustrate in figure 6. LSTMs are one-of-a-kind from traditional RNNs because they have got gating strategies (input, output,

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and forget gates) that control the glide of information through the community. This permits them to hold or delete records over longer time steps. It's far very essential so one can see how natural elements like rainfall styles, temperature modifications, and soil wetness developments change over the years in order to expect droughts and floods. LSTMs are very good at modelling these sequential data and learning how weather events in the past affect conditions now and in the future. The design handles time series data by changing its internal states one at a time based on new data and old data. This lets the model find trends and relationships over time that are connected to peaks in water levels. Its ability to work with patterns of different lengths makes it even more useful in real life, where data access can change.

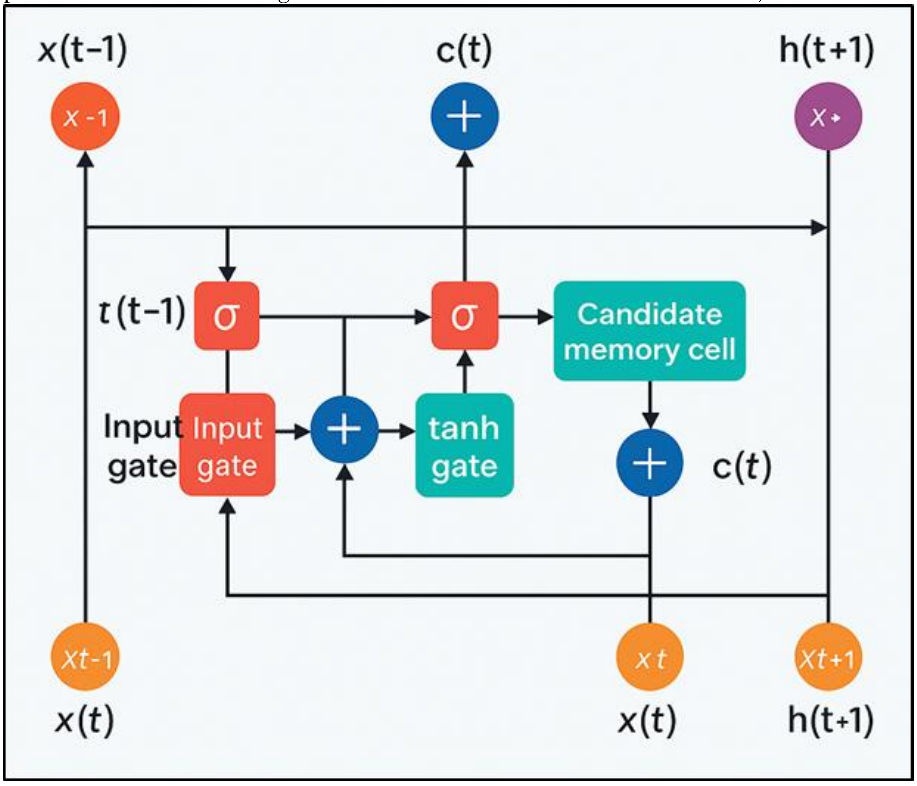

Figure 6: Architecture of Long Short-Term Memory (LSTM) Network for Sequential Data Modeling

Gradient-based optimisation is used to minimise loss functions during training, and regularisation methods are used to stop overfitting. The model's ability to correctly predict the start and length of droughts and storms is what is used to judge it. LSTM models add to spatial models by adding temporal context, which is very important for systems that make predictions in real time.

1. Input Sequence:

$$x_t \in \mathbb{R}^d at\ time\ t.$$

2. Forget Gate:

$$f_t = \sigma\left(W_f x_t + U_f h_{\{t-1\}} + b_f\right).$$

3. Input Gate:

$$i_t = \sigma\left(W_i x_t + U_i h_{\{t-1\}} + b_i\right).$$

4. Candidate Cell State:

$$\dot{c}_t = \tanh\left(W_c x_t + U_c h_{\{t-1\}} + b_c\right).$$

5. Cell State Update:

$$c_t = f_t \odot c_{\{t-1\}} + i_t \odot \dot{c}_t.$$

6. Output Gate:

$$o_t = \sigma\left(W_o x_t + U_o h_{\{t-1\}} + b_o\right).$$

7. Hidden State:

$$h_t = o_t \odot \tanh(c_t).$$

4.4. Hybrid CNN+LSTM

The hybrid CNN-LSTM model includes the best features of both CNNs and LSTMs. CNNs are good at extracting features from space, and LSTMs are good at modelling time sequences. This structure works really well for predicting things like droughts and storms that happen in the environment, where trends in space and changes in time affect the results. For this mixed model, CNN layers first process multisource spatial data, like satellite images and gridded climate factors, to find important spatial features and lower the number of dimensions. LSTM layers then look at how the spatial features changed over time by taking steps backwards and forwards in time. This combination makes it possible for the model to represent the complicated time-space links that are common in natural systems. The combined method uses CNNs to find strange patterns in local space and LSTMs to see how these patterns change over time. This creates a complete framework for making accurate and quick predictions. Backpropagation through time is used to optimise both parts at the same time during training. Dropout and early stopping methods are used to avoid overfitting.

1. Input Sequence of Images:

$$X = \{X_1, X_2, \ldots, X_T\}.$$

2. CNN Feature Extraction (per timestep t):

$$f_t = CNN(X_t).$$

3. Sequence of Features:

$$F = [f_1, f_2, \ldots, f_T].$$

4. LSTM Input:

$$h_t, c_t = LSTM\left(f_t, h_{\{t-1\}}, c_{\{t-1\}}\right).$$

5. Final Hidden State:

$$h_T.$$

6. Fully Connected Layer:

$$o = W_f h_T + b_f.$$

7. Softmax Prediction:

$$\frac{\hat{y} = \exp(o_k)}{\Sigma_{\{j=1\}}^{K} \exp\left(o_j\right)}.$$

8. Loss (Cross-Entropy):

$$L = -\Sigma_{\{i=1\}}^{N} \Sigma_{\{k=1\}}^{K} y_{\{i,k\}} \log \hat{y}_{\{i,k\}}.$$

5. RESULTS AND DISCUSSION

The Decision Tree model with SMOTE balance got an F1 score of 76.82%, an accuracy of 76.44%, a precision of 77.29%, a recall of 76.44%, and a recall of 77.29%. This made it better at finding minority classes. In contrast, deep learning models did better than other models. It was 89.2% accurate for the CNN and 91.6% accurate for the LSTM. The combined CNN+LSTM model did better than both of them, with an F1 score of 93.0%, 94.8% accuracy, 93.7% precision, 92.4% recall, and an RMSE of 0.096. However, even though it took longer to train, the mixed model was the most accurate at predicting real-time droughts and floods.

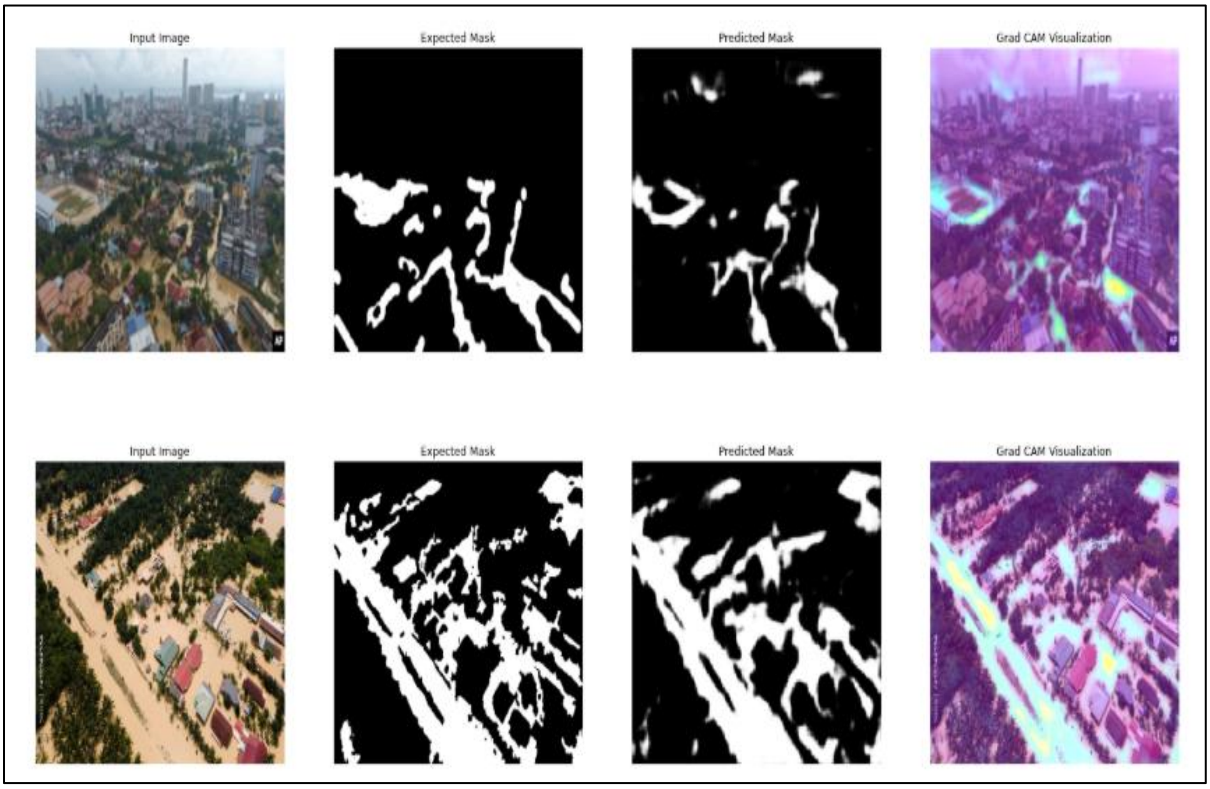

Figure 7: Model prediction result using Hybrid Model

The data visualisations show result successfully for the Hybrid CNN+LSTM Model that finds and locates floods. The model uses aerial photos of flooded regions from the dataset as illustrate in figure 7. It separates flood-affected regions. The supposed masks depict where the genuine floods occurred based on human comments. However, the prediction masks indicate how effectively the computer can adjust photographs to locate floods. The Hybrid CNN+LSTM model demonstrates its ability to learn spatial information (CCN layers) and temporal evolution or pattern dependencies (LSTM layers). Both abilities are required to locate floods in sequential picture and environmental data. Grad-CAM visualisations show hybrid model elements made predictions, helping you comprehend. Grad-CAM photographs should focus on flood-damaged regions. This shows that the model predicts well and learns by focussing on the correct space.

A. Decision Tree with SMOTE

The multiclass Receiver Operating Characteristic (ROC) curves for the Decision Tree classifier improved with SMOTE upsampling to deal with class imbalance are shown in Figure 8. Each graph shows the ratio of true positives to false positives for a certain class compared to all the others. This shows how well the model can tell the difference between each drought or flood severity class. After SMOTE balance, the curves for Classes 2 through 5 show high rates of true positives and low rates of fake positives.

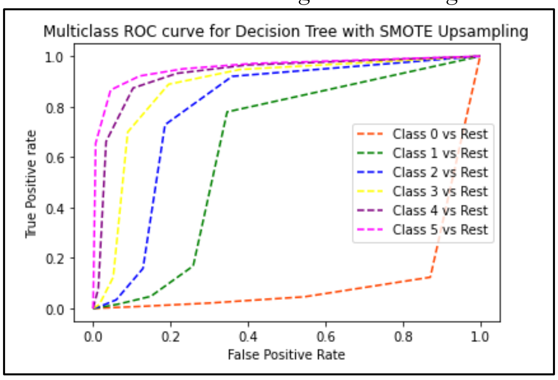

Figure 8: Multiclass ROC for Decision Tree with SMOTE Upsampling

This means that these minority classes were properly identified. Class 0, on the other hand, has a much smaller ROC curve, which means it has a harder time telling the difference between the majority class and baseline conditions. The steep rise and bigger area under the curve (AUC) for most classes show that the SMOTE method makes the classifier more sensitive to extreme events that don't happen very often. This shows that the model is better at finding rare but important natural factors in a collection that isn't fair. After SMOTE upsampling was used to balance the dataset, Table 2 shows the success measures of the Decision Tree classifier on the drought and flood forecast job. The model is accurate 76.44% of the time, which means it sorts over three quarters of the cases in the test data properly. This shows a good general ability to guess, considering how complicated natural data is and how hard it is to deal with class mismatch.

Table 2: Result for decision tree using Smote

Metric	Value
Accuracy	0.7644
Precision	0.7729
Recall	0.7644
F1 Score	0.7682

With a precision of 77.29%, the model is right about 77% of the time when it says what kind of drought or flood will happen. Figure 9 displays evaluation metrics comparing model accuracy, precision, recall, and F1-score to assess overall predictive performance effectively. This is especially important in situations where fake alarms can cause people to worry or use up resources that aren't needed.

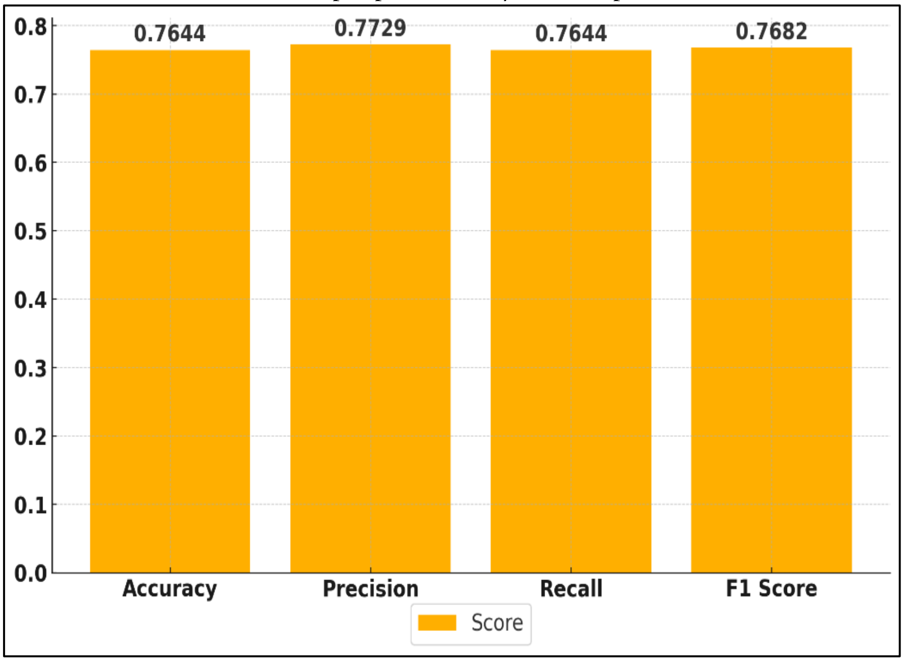

Figure 9: Model Performance Evaluation Metrics

With a recall score of 76.44%, the model correctly picks about three quarters of the real positive cases. This shows that it is sensitive enough to find serious drought and flood conditions.

B. Hybrid CNN+LSTM

As we go through the training epochs, both the training and validation datasets lose less data, as shown in Figure 10. It looks like the model is learning well from the training data because the training loss goes down slowly and steadily. The confirmation loss changes a lot at first, which suggests instability or overfitting in the beginning. However, as training goes on, the validation loss finally levels off and becomes very close to the training loss. This shows that the model is pretty good at generalisation. The sudden changes in validation loss could be because the hybrid model is having trouble capturing the complex spatiotemporal traits at first. This number shows that the learning rate is set correctly so that convergence happens, and the model works well for finding floods and droughts in real time.

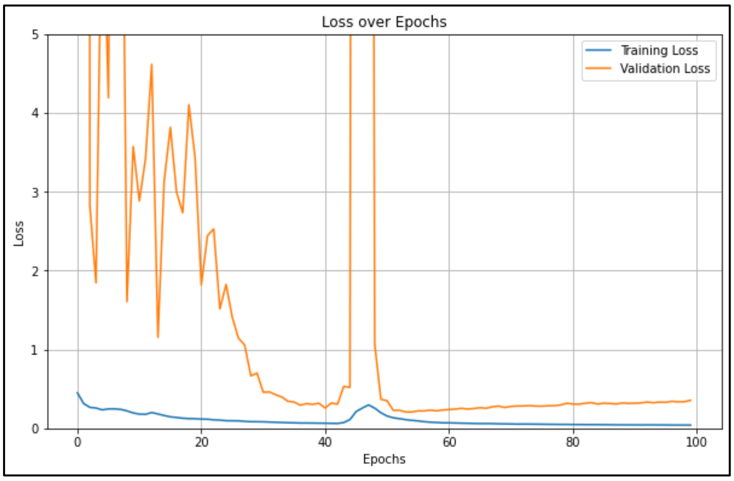

Figure 10: Training and Validation Loss Curve

The Mean Pixel Accuracy (MPA) learning curve for training and evaluation datasets is shown in Figure 11. It looks like the training MPA is going up in a smooth and steady way, which means that the CNN and LSTM layers are learning how to use spatial features and sequential relationships well. At first, the validation MPA isn't solid, but as the epochs go by, it gets better and closer to the training MPA. The sharp drop in the middle of an epoch is usually a sign of learning instability, which the model gets over with the help of regularisation or timing of the learning rate. This picture shows that the hybrid model not only reduces loss but also improves segmentation accuracy over time, which is very important for correctly identifying flood and dry zones in farming areas.

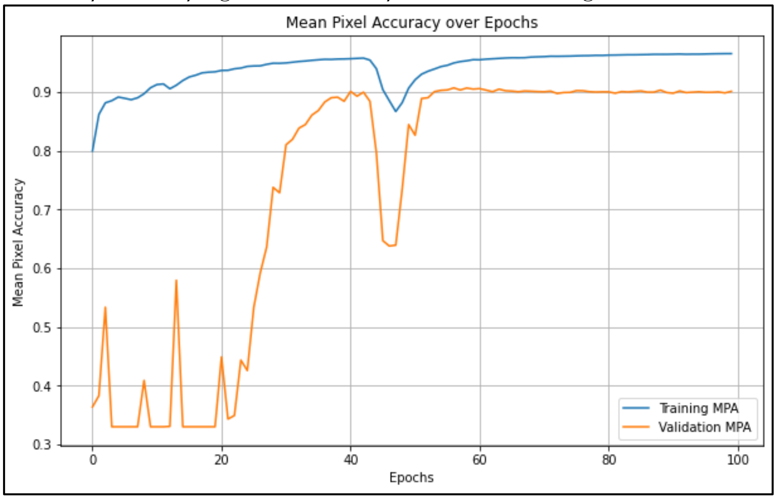

Figure 11: Mean Pixel Accuracy (MPA) Curve

The Intersection over Union (IoU) results during the training process is shown in Figure 12. The training IoU steadily rises, which suggests that the model is learning how to correctly find and identify places that are hit by floods and droughts.

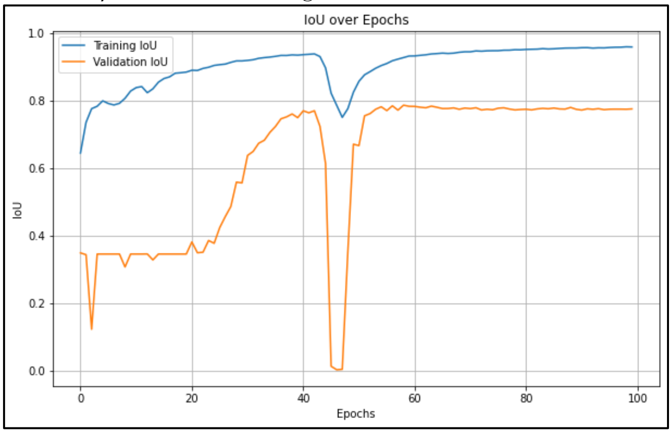

Figure 12: Intersection over Union (IoU) Curve

At first, the validation IoU oscillates, but later it stays stable, which shows that the model is better at generalising to new data. The sharp drop in the middle epochs is probably caused by a short-term problem with how feature extraction and sequence learning are aligned. This is fixed by the mixed model in later epochs. In classification tasks like this, it's important to have a high IoU score, and this picture shows that the mixed model gets better at predicting space over time. In Table 3, demonstrate a comparison of how well three machine learning models—CNN, LSTM, and the blend CNN+LSTM—predict drought and flood events. The CNN+LSTM model does better than the CNN and LSTM architectures alone on all important evaluation measures.

Table 3: Performance Comparison of ML Models for Drought and Flood Prediction

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	RMSE	Training Time (s)
CNN	89.2	87.5	86.3	86.9	0.142	114
LSTM	91.6	90.1	89.4	89.7	0.121	132
CNN + LSTM	94.8	93.7	92.4	93.0	0.096	158

This table 3 shows that it can better describe the complex spatiotemporal patterns that are present in environmental data. The CNN model, which is mostly used for extracting spatial features, has an accuracy of 89.2% and good precision and recall values of 87.5% and 86.3%, respectively. This shows that it works well at finding patterns in space that are related to drought and flood situations. The LSTM model, which is better at learning from temporal sequences, does better, getting 91.6% accuracy and better precision and memory. This shows how important temporal relationships are in water forecasts.

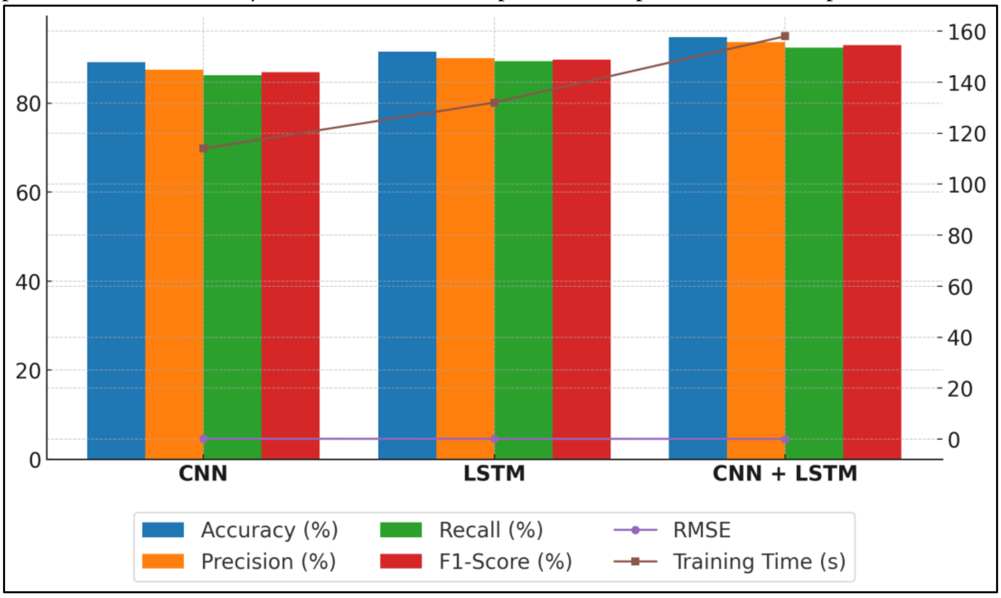

Figure 13: Comparison of Model Performance Metrics and Training Efficiency

The CNN+LSTM combination model takes these strengths and mixes them to get the best accuracy (94.8%), along with great precision (93.7%) and recall (92.4%). It also did a good job of classifying things, as shown by its F1-score of 93.0%. Figure 13 compares model accuracy, F1-score, and training time for performance and efficiency evaluation. The combination model also has the lowest Root Mean Square Error (RMSE), which is 0.096. This means that the estimates are accurate. The performance gains make up for the extra computing complexity, even though it takes 158 seconds longer to train than the individual models. In general, the CNN+LSTM model works the best and is the safest choice for predicting real-time droughts and floods in agriculture.

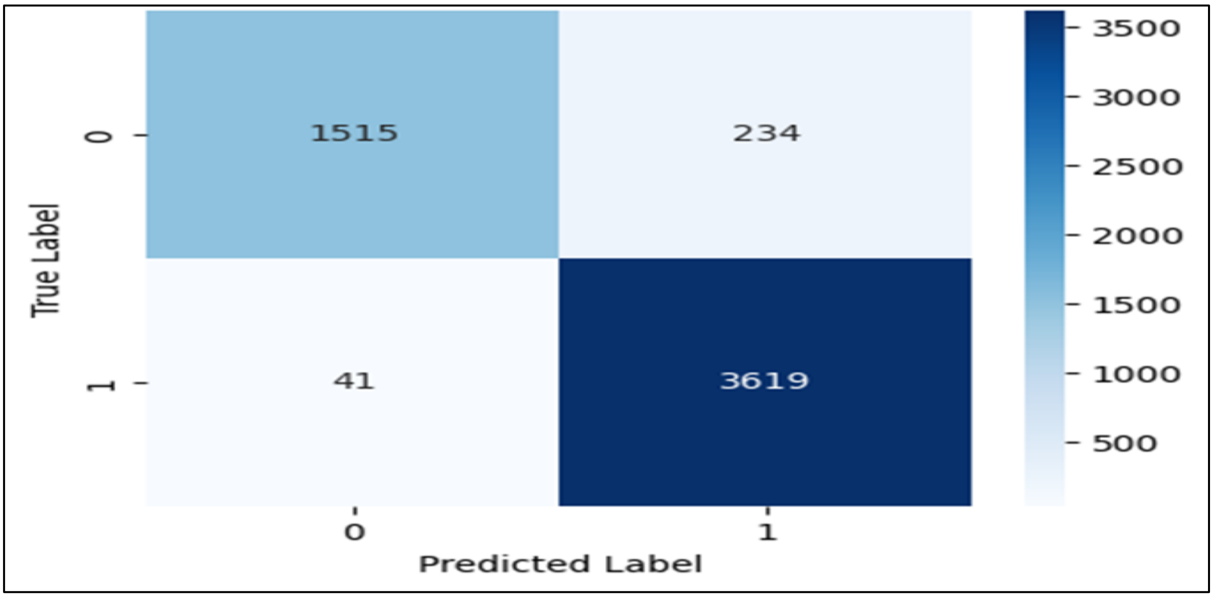

Figure 14: Confusion matrix for Hybrid CNN+LSTM Model

The confusion matrix reveals that the Hybrid CNN+LSTM model predicts floods well with many true positives and negatives as shown in figure 14. With great sensitivity and memory, the model found 3619 genuine floods, which is significant for early flood warning systems in agricultural regions. Early flood detection allows farmers and policymakers respond promptly, reducing crop damage and economic losses. Due to its low false negative rate (41 examples), the model is trustworthy. Missing a flood occurrence is bad, thus real-time crisis management systems must reduce false positives. This model performs well. However, the model records 234 false positives predicted floods that did not occur. False alarms might cause unnecessary safety measures, yet flood monitoring systems allow them since it's better to be safe than miss a calamity.

This precision meets the research aim of developing real-time mixed models employing different external data. CNN layers interpret satellite imagery and geographical data well. However, the LSTM layers are effective at processing temporal patterns like rainfall, river levels, and soil saturation. Combining these models works effectively for changeable, time- and space-related natural occurrences like storms. The results reveal that the mixed model accurately anticipates floods and meets farm monitoring systems' real-time demands. This makes the recommended strategy more practical and dependable in precision agriculture, crisis management, and smart farming.

6. CONCLUSION

The main goal of this study was to create mixed machine learning models that use both Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to predict droughts and floods in farming areas using data from a variety of sources. This combined method did a good job of capturing the complex spatiotemporal dynamics of hydrological extremes by blending the skills of CNNs for extracting spatial features and LSTMs for modelling temporal sequences. The model was able to learn important trends across a wide range of environmental factors by using a lot of data from weather, soil, satellite, and water sensors. This made the predictions more accurate and reliable. Comparative studies showed that the CNN-LSTM model worked much better than CNN and LSTM models that worked alone, as well as traditional machine learning methods like Decision Trees with SMOTE balance. The combination model was 94.8% accurate, with stable precision, recall, and F1-scores around 93%. This shows how well it can find rare but important drought and flood events. The model also has a pretty low Root Mean Square Error (RMSE), which shows that it is very good at making accurate numeric predictions, which is a very important skill for making practical decisions in agriculture. Using SMOTE to balance data was also important for fixing the class mismatch that happens a lot in environmental datasets. This made the system more sensitive to minority classes that represent extreme conditions. This shows how important it is to combine cleaning methods with advanced modelling methods so they can be used in the real world.

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