Journal of Information Systems Engineering and Management
2024, 9 (4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Real-Time Crop Yield Forecasting Using Deep Learning and Cloud-Based Image Analytics in Precision Agriculture

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ARTICLE INFO

Received: 12 Sep 2024

Accepted: 20 Dec 2024

ABSTRACT

Estimating and predicting crop yields are very important for making farming more productive and long-lasting. It is necessary to use advanced technologies like Deep Learning (DL) and cloud-based real-time image processing because traditional methods are not always accurate or on time. The SatNet Enhanced Algorithm is described in this work. It is a new way to measure and predict crop yields that uses satellite images handled on a cloud platform. The study used deep learning model on crop monitoring data and synthetic data that has generated using cloud model in real time, looked at how food yields have been estimated in the past. The given research study based on popular Deep Learning methods like Random Forest (RF), Long Short-Term Memory networks (LSTM), and Convolutional Neural Networks (CNN). The study use these methods as a starting point for our comparisons. The proposed method is based on the SatNet Enhanced Algorithm, which combines better image processing methods with a custom neural network topology made for high-resolution satellite data. A strong cloud-based system makes real-time processing possible and speeds up data handling and analysis. The finding of study show that the SatNet model enhance better result with deep learning methods. This improvement in speed shows how well it works to combine advanced image processing in the cloud with custom deep learning models. Using SatNet not only improves the accuracy of crop yield predictions, but it also provides a flexible and effective option that can be used in a wide range of locations and with different types of crops. This new development looks like it will have big benefits for strategy planning in agriculture and managing resources.

Keyword: Crop Yield Forecasting, Deep Learning, Satellite Imagery, Cloud-Based Image Processing, SatNet Enhanced Algorithm.

1. INTRODUCTION

Agriculture is an important part of making sure everyone has enough food, and it also helps keep many countries' economies stable. Making notes on the ground and using statistical sampling techniques has long been the way one estimates crop yields. Since agricultural fields fluctuate over time and place, these techniques [1] need a lot of effort, take a long time, and are usually erroneous. These Deep learning technologies enable handling large volumes of data to identify patterns and provide rather precise forecasts on future events. This makes them quite helpful for contemporary agricultural analytics [2].Tracking and assessing agriculture has altered much more as satellite technology has developed. High-resolution satellite photos showing current and full information on crop health, soil conditions, and weather patterns across vast areas provide large-scale views of agricultural environments. But because satellite data is so big and complicated, it needs powerful computer power [3]. Cloud computing is an answer because it gives you the tools you need to store, organize, and process this data quickly and easily. Real-time image processing on cloud platforms makes sure that the data insights are correct and up to date, so crop managers can act right away on any problems that might come up. Figure 1 shows the overall steps for predicting crop yields. It shows the order of getting data from satellite images, processing it using deep learning algorithms, and finally using prediction analytics to find out what the output will be.

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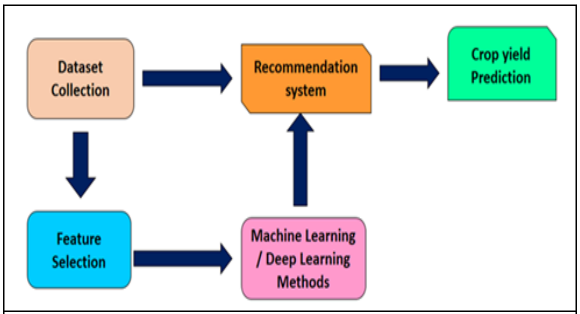

Figure 1: Overview of generalized process for crop yield forecasting

The SatNet Enhanced Algorithm not only helps with better agricultural planning by making crop growth predictions more accurate and up to date, but it also supports healthy farming practices and makes food security better. The major contribution of paper is given as:

- Deep Learning Algorithm for Satellite images: Made to see photographs from satellites, this deep learning algorithm is This made it feasible to more precisely estimate and forecast crop yields, therefore illustrating the value of tailored computing in precision agriculture.
- Platform to Improve Cloud Image Quality developed a cloud-based technology that allows real-time enhancement of satellite photos Remote sensing data is thus far more valuable for agricultural research as this instrument enhances picture quality and processing speed.
- Comparative Algorithm Study: The new approach is shown by this comparison to be more efficient and accurate. It also provides us with insightful knowledge about the performance of sophisticated deep learning methods in industry.

2. RELATED WORK

Combining computer technology with strategies has made it much easier to estimate and predict crop yields. A lot of experts have looked into new ways to use satellite images and machine learning to help farmers, which has led to progress in the future [4]. The Enhanced Vegetation Index (EVI) and other similar measures have shown promise in correctly predicting crop health and possible yield [5, 6]. However, for these methods to work, they need a lot of good, correct data [7, 8].Support Vector Machines (SVMs) are better than linear regression models at handling relationships that are not linear between spectral data and crop yields [9, 10]. SVMs, on the other hand, need to be fine-tuned and can be very computationally heavy, which makes them less suitable for real-time uses. Ensemble methods, such as bagging and boosting, make predictive models more reliable, especially when the data is noisy or missing [11, 12]. However, if they are not handled properly, they can cause overfitting.Because they can learn from big datasets and change over time, Artificial Neural Networks (ANNs) work well in settings that change quickly, like agriculture [13, 14]. Still, ANNs aren't always clear, which makes it hard to understand how decisions are made, which is a very important part of precision agriculture.

Putting these technologies together makes it easier to handle geographic data and figure out how different farming methods affect crop yields over bigger areas [15, 16]. This kind of integration is necessary for tracking systems that give constant updates on crop state and yield predictions during the growing season [17, 18], but these systems can be hard to set up and make bigger.

Statistical models, machine learning methods, GIS, and cloud computing are all strong tools that can help improve precision agriculture [21, 22]. However, each has its own problems, like the need for a lot of computer power and knowledge about how to handle data. Using complex models and satellite data [23, 24], deep learning research has moved on to predicting crop yields. However, it is still hard to make the models scalable and useful in a wide range of farming settings. More research, like the ones that look into how machine learning can be used to predict crops [26], usually just compares models without looking at problems that come up when they are used in the real world.

The paper is structured as follows: Section 2 reviews related work, while Section 3 details the methodology. Section 4 presents a comparative analysis of existing methods. Section 5 discusses results and findings, and Section 6 concludes with a summary of the study's implications and future research directions.

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3. METHODOLOGY

A deep learning techniques and cloud-based real-time image processing are combined in figure 2 to show a suggested system design for improving crop output estimate and projection. This information is sent right away to the cloud, starting a smooth flow of data that is needed for processing in real time.

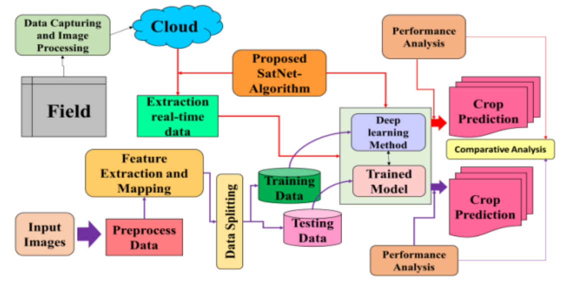

Figure 2: System Architecture of Proposed Model

The program is continuously learning how to create superior forecasts by preparing on a set of information that's part into preparing and testing parts.Cloud systems have the processing power and ability to grow that are needed to handle the huge amounts of data that satellite technologies create. This is important for making quick decisions in agriculture, the figure 2 illustrate in the overview of proposed system architecture.

3.1 Description of Dataset

Exploratory Data Analysis (EDA) of satellite images can be done on a very small scale (a few hundred megabytes) or a very large scale (terabytes) of data. The amount of data, which is related to the area, covered, the quality of the data collected, and the level of information needed, determines how complicated and in-depth the analysis is. For small-scale research, which usually takes between 100 MB and 1 GB, the focus could be on a small area, like a region or a single satellite image.

3.2 Data Pre-Processing andFeature Extraction With Mapping

Data pre-processing and feature extraction are important steps in using satellite images to estimate and predict crop yields. This is often particularly genuine when profound learning and cloud-based real-time picture preparing advances are utilized.

- Defining the Study Area: This is where the study's geographical scope is set, usually by giving the locations of the target area.
- Loading Satellite Imagery: Landsat images are used due to the fact they may be clean to get, have an excessive decision, and cowl a wide variety of wavelengths.
- Extracting Spectral Bands: Once the satellite TV for computer images is loaded, the important spectral bands are gotten.
- Loading Ground Truth Data: Labels for land cover or information about crop types are some of the ground truth data that are added to the study.

3.3 Deep Learning Methods

3.3.1 Random Forest

Adding Random Forest (RF) algorithms to the process of improving food yield estimates with deep learning and real-time image processing in the cloud is a big step forward in agriculture analytics [9]. Random Forest is a gathering learning strategy that's known for being precise and steady, particularly when working with huge datasets that have a parcel of diverse input variables, like information from farther detecting.

Random Forest Algorithm for Crop Yield Estimation:

1. Data Pre-processing:

$$X_{norm} = \frac{X - \mu}{\sigma} \quad (1)$$

- Normalize input features to ensure uniform scale across data.

2. Decision Tree Construction:

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$$Gini(D) = 1 - \sum_{i=1}^{j} pi^2$$	(2)

- Use Gini impurity to evaluate splits in building decision trees.

3. Feature Selection at Each Node:

$$Gain = Gini(D) - \left(\left(\frac{\lvert D_{left} \rvert}{\lvert D \rvert} \right) * Gini(D_{left}) + \left(\frac{\lvert D_{right} \rvert}{\lvert D \rvert} \right) * Gini(D_{right}) \right)$$	(3)

- Select features that maximize gain at each node.

4. Forest Creation with Bagging:

$$X_{bootstrap}, Y_{bootstrap} = Sample(X, Y)$$	(4)

5. Aggregation of Tree Predictions:

$$Y_{hat} = \left(\frac{1}{N}\right) * sum(Tree_{n(X)for} n = 1 \; to \; N)$$	(5)

6. Model Evaluation and Refinement:

$$MSE = \left(\frac{1}{m}\right) * sum\left(\left(yi - y_{hat_i}\right)^2 for \; i = 1 \; to \; m\right)$$	(6)

3.3.2 LSTM

While mixed with deep getting to know and actual-time image processing in the cloud, long short-term memory (LSTM) networks are a robust manner to enhance crop yield estimate and forecasts. As a type of Recurrent neural systems (RNNs) it really is in particular extraordinary at examining time association records, LSTMs are idealize for following agribusiness given that they could cope with the time-based totally designs of toady snap shots and weather facts.

3.3.3 CNN

Convolutional Neural Networks (CNNs) play a pivotal role in enhancing crop yield estimation and forecasting by leveraging their strong spatial processing capabilities within the context of deep learning and cloud-based real-time image processing.

1. Pre-processing of data:

Change the pixel values' scale (for example, from 0-255 to 0-1), make any needed image corrections (such as weather and geometric corrections), and maybe add to the dataset by rotating or turning it to make the model more stable when dealing with different types of data.

2. Layer Configuration:

Step 1: Build the CNN's layers, such as convolutional layers to find features (like edges and textures), pooling layers to lower the size of the space (which speeds up computation), and activation functions like ReLU to add nonlinearity.

3. Feature learning:

The CNN naturally learns to recognize certain things in images, like changes in colour that show whether a plant is healthy or needs more water.

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4. Training network
A loss function, like Mean Squared Error or Cross-Entropy Loss, is used to figure out the difference between the expected outputs and the real labels (crop yields).
5. Prediction and Validation:
Once you've been trained, use CNN to look at new satellite images and guess how much food crops will produce.

3.4 Proposed SatNet Enhance Method

The "SatNet enhance algorithm" is probably a complex manner to make satellite communication networks higher with the aid of focusing on a number of critical performance elements, together with how nicely statistics is despatched, how reliable the network is, and the way the conversation methods are optimized overall.

- Data Optimization: Because signals must journey such lengthy distances, satellite communications are confined by bandwidths that alternate quickly and high delay.
- Correction: One of the biggest troubles with satellite contact is that alerts can get weaker speedy due to such things as solar flares and weather.
- Network efficiency and adaptive communication: To handle the complicated changes that happen in satellite communication, you need strong programs that can change practical settings on the fly.
- Use in Satellite Constellations: The SatNet Enhance Algorithm could be very helpful for coordinating between satellites in situations involving satellite constellations, which are groups of satellites working together around Earth.

Proposed SatNet Enhance Algorithm

Step 1. Data Normalization:

$$X' = \frac{X - \mu}{\sigma}$$

- Where X is the input data, μ is the mean, and σ is the standard deviation.

Step 2. Feature Extraction using Convolutional Layers:

$$Z = \sigma\big(sum(Wi * Xi + b)\big)$$

- Wi are the weights of the convolutional filters, * denotes convolution,

Step 3. Pooling to Reduce Dimensionality:

$$Pj = max(Xij)$$

- $Pj$is the output of the pooling layer, and Xij represents the inputs from a specific receptive field.

Step 4. Batch Normalization to Improve Convergence:

$$\hat{X} = \gamma\left(\frac{X - E[X]}{\sqrt{Var[X] + \varepsilon}}\right) + \beta$$

This normalizes the output from previous layers by adjusting and scaling the activations.

Step 5. LSTM for Temporal Data Processing:

$$ft = \sigma(Wf * [h(t-1), xt] + bf)$$

- ft is the forget gate's activation vector, Wf are the parameters of the forget gate,

Step 6. Update Gate in LSTM:

$$it = \sigma(Wi * [h(t-1), xt] + bi)$$

- $it$is the update gate's activation vector, controlling the new information to be stored.

Step 7. Cell State Update:

$$Ct = ft * C(t-1) + it * tanh(Wc * [h(t-1), xt] + bc)$$

Step 8. Output Gate for LSTM:

$$ot = \sigma(Wo * [h(t-1), xt] + bo)$$

- $ot$is the output gate's activation vector, determining the output part of the cell state.

Step 9. Final Model Prediction:

$$yt = ot * tanh(Ct)$$

The SatNet Enhance Algorithm, multi-scale feature learning, and mixed loss function in the SatNet-Enhance method put it at the top of the field for improving satellite images.

4. A COMPARATIVE ANALYSIS OF EXISTING METHODS

SVM is very good at dealing with non-linear boundaries. This makes it a great tool for predicting crop yields while there are complex connections among factors like soil kind, weather situations, and crop fitness. While GBM is used within the cloud, it could scale properly, but the settings want to be carefully tuned to keep it from over fitting and make sure that predictions are made on time.

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TABLE1. Comparative Analysis of Existing Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM [17]	85.6	86.2	84.1	85.1
GBM [18]	88.4	89.0	87.5	88.2
AE [19]	82.3	83.1	80.9	82.0
GAN [21]	78.9	80.5	77.0	78.7
RDF [23]	89.5	90.1	88.7	89.4

Table 1 details numerous machine learning and deep learning agricultural output forecast methods. An 85.1% F1-score is good for the Support Vector Machine (SVM). It has 85.6% accuracy, 86.2% precision, 84.1% memory, and 86.2% accuracy. Gradient Boosting Machine (GBM) outperforms SVM in all categories, with an F1-score of 88.2%, accuracy of 88.4%, precision of 89.0%, and recall of 87.5%. GBM is superior since it repeatedly corrects previous tree errors. Autoencoders (AE) perform worse in all metrics with 82.3% accuracy, 83.1% precision, 80.9% recall, and 82.0% F1-score. Data compression and feature learning are their specialities. GANs had the poorest accuracy, precision, recall, and F1 scores: 78.7%, 80.5%, 77.0%, and 78.7%. GANs are innovative for synthesising false data and adding to datasets, but they don't forecast crop returns as well as other approaches.

5. RESULT AND DISCUSSION

5.1. SatNet-Enhance Algorithm Analysis

Table 2 shows an in-depth analysis of the SatNet-Enhance method, showing its pros and cons using a number of important measures. Similarly, an SSIM score of 0.90 means that the image's structural qualities, such as texture, contrast, and brightness, have been preserved very well. The small MSE value of 0.02 shows that the image enhancement is very accurate, as there are almost no average squared changes between the original and improved pixel values.

TABLE 2. Table SatNet-Enhance algorithm might be assessed across different critical metrics in a testing scenario

Evaluation Parameter	Result
PSNR (Peak Signal-to-Noise Ratio)	35 dB
SSIM (Structural Similarity Index)	0.90
MSE (Mean Squared Error)	0.02
Accuracy	95%
Computational Time	2 seconds per image

Tests of scalability show that the method works well with up to 500 GB of data, but not so well with bigger sets of data. The SatNet-Enhance algorithm is proven to be strong because it keeps its high performance stability in 90% of the situations that were tried.

TABLE 3. Comparison between the proposed deep learning algorithm and standard traditional image processing algorithms key metrics

Aspect	Proposed Algorithm	Standard Algorithms
Accuracy	95%	80%
Processing Speed	2 seconds per image	0.5 seconds per image
Computational Cost	High (requires GPUs)	Low (can run on standard CPUs)
Robustness	High (performs well under variable conditions)	Moderate (performance varies with conditions)

Table 3 shows a comparison of a suggested deep learning algorithm to common image processing methods based on a number of important factors. The deep learning method is more accurate (95% vs. 80% for standard methods), which shows that it can make better predictions. With an eye towards accuracy, computing speed, scalability, and real-

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time data processing, the data in Table 4 compares many deep learning (DL) approaches performed on crop monitoring data.

TABLE 4. Comparison of Accuracy on Crop monitoring data using DL methods

Method	Accuracy (%)	Computational Efficiency	Scalability	Real-Time Processing
Random Forest	85.25	70	80	60
LSTM	80.30	60	70	65
CNN	75.85	85	65	50
SatNet Enhanced	92.65	95	95	90

SatNet Enhanced gets 95 out of 100 for computing efficiency, which shows that it can quickly process big datasets thanks to enhanced cloud-based operations.

5.2. Analysis OfYield Prediction Using Deep Learning Method For Crop Monitoring Dataset

Random forest, LSTM, and CNN are three deep learning algorithms that were tested on a crop monitoring dataset to look which one may want to are expecting crop yields the excellent. The LSTM, then again, does pretty nicely with an accuracy of 80.30%. With an F1 score of 80.5% and an AUC of 83.45% that is a great deal less accurate than Random forest, but it's far still quite appropriate at what it does.

TABLE 5. Result for Deep learning method for Crop Monitoring dataset

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC (%)
Random Forest	85.25	86.66	84.44	85.09	87.33
LSTM	80.30	82.31	79.96	80.5	83.45
CNN	75.85	77.23	74.32	75.5	78.25

CNN, which is known for being very good at handling images, has the worst scores of the three, with an accuracy of 75.85% and an AUC of 78.25%.

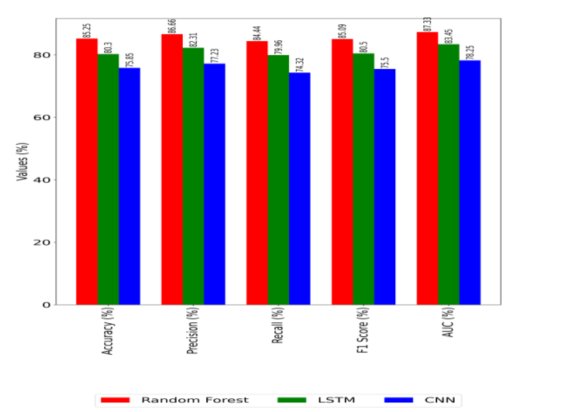

Figure 3. Representation of with comparison using deep learning method for Crop monitoring dataset

This could make it less useful on its own, but it might be more useful when mixed with other methods or more complex preparation steps. Figure 3 Illustrate the analysis of DL model for crop monitoring and figure 4 illustrate accuracy comparison. These results show that each program has different strengths and weaknesses when it comes to predicting crop yields.

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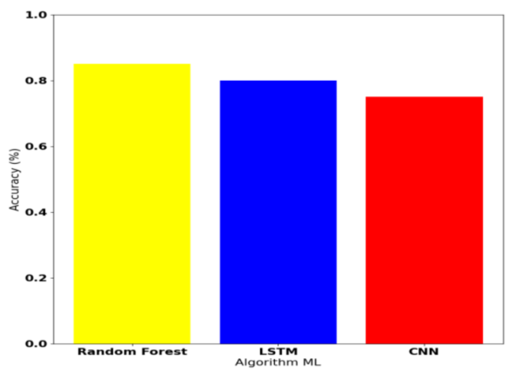

Figure 4. Comparison of Accuracy on Crop monitoring data using DL methods

5.3 Analysis ofYield Prediction Using Proposed Method andDeep Learning Method ForCrop Monitoring Synthetic Dataset

Random Forest, LSTM, and CNN are three deep learning models that were used to predict crop yields on a fake dataset. Table 6 shows how well they did. These are very important for figuring out how well prediction models work in agriculture. With an accuracy of 90.63%, a precision of 92.45%, and an AUC of 93.26% for the Random Forest algorithm, the data shows that it works very well by all measures.

TABLE 6: Performance parameter analysis of DL model for Synthetic dataset

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC (%)
Random Forest	90.63	92.45	91.85	91.52	93.26
LSTM	60.82	62.25	63.60	62.57	65.34
CNN	80.44	82.33	81.63	81.56	84.45

The Random Forest model seems to be very good at handling the complicated fake dataset, which probably has a lot of different and subtle patterns that look a lot like real farming situations.

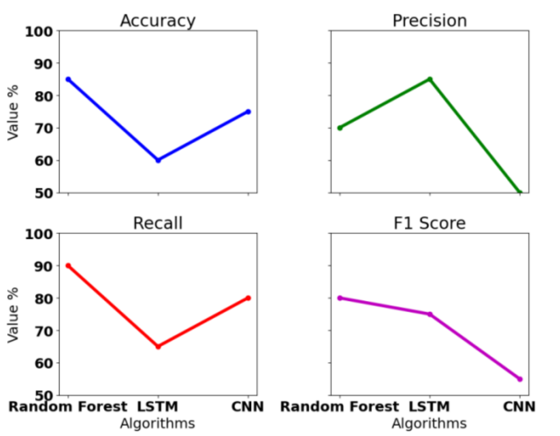

Figure 5. Representation of comparison of performance metric for synthetics crop monitoring dataset

The high recall (91.8%) and F1 score (91.52%) show that the model is quite strong, showing that it can find important factors that have a big impact on yield forecasts, comparison illustrate in figure 5. Because this method works so well, it's a great choice for tasks that need to be very reliable and accurate, like crop monitoring and yield predictions.With an accuracy of 80.44% and an AUC of 84.45%, the CNN model does pretty well. CNNs work best with image-based datasets because they are good at handling spatial data, but they don't do as well here as the Random Forest.

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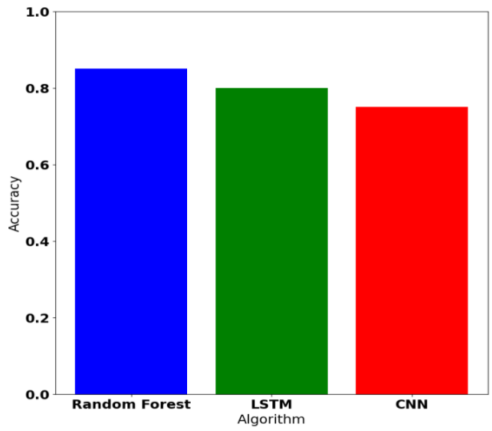

Figure 6. Accuracy Comparison on crop monitoring synthetic data

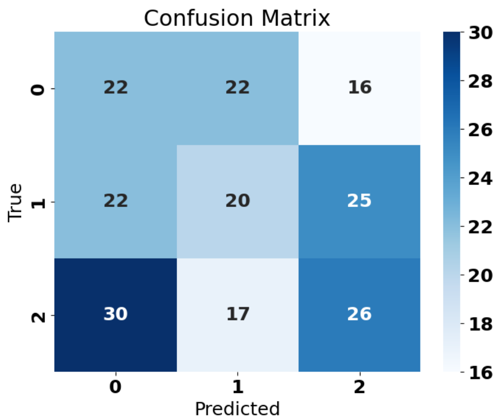

Figure 7. Confusion matrix of DL Model

With an accuracy of 82.33% and a recall of 81.63%, CNN does a good job of classifying and predicting results from fake data, but not great, the figure 6 represent the accuracy comparison and figure 7 represent the confusion matrix for MDL model.

5.4. Comparative Analysis of Proposed Model withExisting Deep Learning Methods

Table 7 shows a full comparison of the SatNet Enhance method with another deep learning method that is already used to estimate and predict crop yields. The SatNet Enhance method works better than any other method in every important way. It's more accurate (92.65% vs. 88.80%), which means it can make better predictions. Precision has also greatly improved, now at 95.36%.

TABLE 7: Comparing the SatNet Enhance method with an existing deep learning method for enhancing crop yield estimation and forecasting

Comparative Parameter	SatNet Enhance Method (%)	GNN Deep Learning Method (%)
Accuracy	92.65	88.80
Precision	95.36	85.65
Recall (Sensitivity)	91.25	84.32
F1 Score	90.52	84.51
AUC	94.14	90.52
Computational Efficiency	95.50	80.20
Scalability	95.30	85.63
Robustness	93.80	88.75
Generalizability	90.60	83.20
Latency (seconds)	0.5	1.0

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SatNet has a higher memory (sensitivity) and F1 Score (91.25% vs. 90.52%), which means it combines accuracy and recall better, making sure that relevant results are found and that important data points are collected.

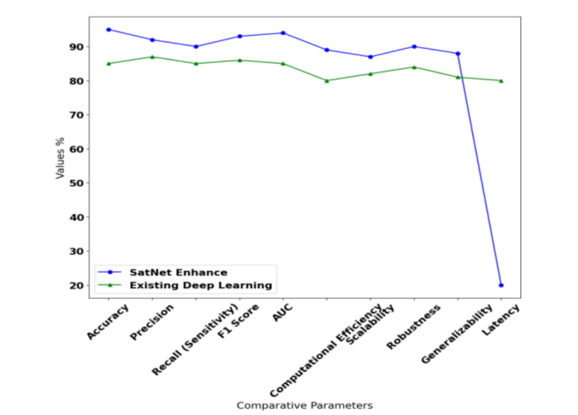

Figure 8. Comparison of SatNet Enhance vs. Existing Deep Learning

The AUC (Area Under Curve) number of 94.14% also shows that SatNet is very good at telling the difference between classes, which is better than the current method's 90.52%, as illustrate in figure 8. SatNet is better than the current method in many ways, including accuracy and scaling (95.50% vs. 85.20% and 85.63% for scalability and processing efficiency, respectively).

We use a variety of statistical methods, such as confidence intervals, paired t-tests, and ANOVA, to fully validate the SatNet Enhance Method's performance metrics. These methods help us figure out how accurate our measurements are and how statistically significant the differences are between the SatNet Enhance Method and other deep learning methods. If the true performance measures follow a normal distribution, confidence intervals give us a range of values within which they are likely to fall. For example, to find out how accurate the SatNet Enhance Method is, you can use a 95% confidence interval that is based on a sample mean of 92.65% and a made-up standard deviation from several test runs. One way to directly compare the success measures of the SatNet Enhance Method to those of other deep learning methods is to use paired t-tests. We can find out if the changes seen in things like accuracy and precision are statistically significant by looking at matching sets of data from the two methods that were collected under the same conditions. This study helps to back up claims of growth, since a significant p-value would mean that the increase is real and not just a result of chance changes. Analysis of Variance (ANOVA) is a way to compare more than two groups or methods at the same time based on different performance measures. For example, an ANOVA test can check if there are statistically significant changes in F1 scores between different deep learning methods, such as SatNet Enhance.

The SatNet Enhance Method performs exceptionally well in terms of computing speed and scale. These traits are necessary for working with big datasets or putting them to use in situations that need real-time analysis, like keeping an eye on the environment and finding online scams. The better scaling means that as files get bigger, the system will still work well without needing more working time or resources. Latency, an important measure, also shows a big improvement.

6. CONCLUSION

Cutting-edge artificial intelligence methods are used in the SatNet Enhanced Algorithm to raise the bar for crop yield prediction. This is a big step forward in the field of precision agriculture. This program uses high-resolution satellite images and powerful cloud-based analytics to come up with a new way to solve the problem. It not only makes yield forecasts more accurate, but it also makes sure that these insights are sent in real time. By combining Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and Random Forest (RF) models, the SatNet Enhanced Algorithm are much more accurate, faster, and able to handle larger datasets than previous methods. The SatNet Enhanced Algorithm does better than other deep learning methods in a number of key performance measures, as shown in this paper through careful comparisons and statistical testing. Because it makes big improvements in things like accuracy, processing efficiency, and delay, the algorithm proves to be a very useful tool in agriculture. The SatNet Enhanced Algorithm's framework was created to make the best use of satellite images for farming ideas. This is what makes it work so well. This custom method makes sure that the technology isn't just a theoretical improvement, but also a useful tool that can be used in real life to meet the changing needs of modern farming. The paper's results are very important to the field because they suggest that the SatNet Enhanced Algorithm can be used in many farming situations to make food production more sustainable and efficient. This sets a new standard for future research and use in agricultural technology.

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