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Crop Yield Estimation Using Deep Learning and Satellite Imagery

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Abstract: For efficient resource management and to guarantee food security, crop yield estimates must be accurate. Deep learning techniques combined with satellite imagery have become a potent method for predicting crop yields in recent years. Deep learning algorithms can extract Data from satellites to provide spatial and temporal information that can be used to analyze crop development patterns and environmental factors. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two examples of these methods. For a precise estimate of crop production, satellite photography offers useful information on soil characteristics, meteorological conditions, and vegetation indices. The application of deep learning with satellite imagery for crop yield estimation is discussed in general terms in this study, including data collection, pre-processing, model selection, feature extraction, yield prediction, and model validation. The recommended method creates a comprehensive agricultural yield prediction system that links raw data to projected crop yields by fusing deep learning and data mining approaches. Incorporating the Tweak Chick Swarm Optimization method for data pre-processing, the proposed model combines the Visual Geometry Group (VGG) Net classification algorithm with a discrete deep belief network. The model outperforms other models by accurately capturing the baseline data distribution, resulting in an accuracy rate of 97% for predictions.

Keywords: *Crop yield estimates; Satellite imagery; production of crop; Data mining; Data collection; Deep learning; Convolutional neural networks (CNNs); Visual Geometry Group (VGG)*

1. Introduction

For efficient agricultural management, guaranteeing food security, and making wise decisions about resource allocation and market forecasting, accurate and timely estimation of crop yields is essential. Crop yield estimation has historically depended on time-consuming field surveys and statistical models [1].

Deep learning methods and the accessibility of satellite imagery have, however, created new opportunities for more accurate and effective agricultural yield estimates. Large-scale yield estimation and understanding the impact of the variability of agricultural growing circumstances are critical [2]–[4] due to the increased frequency of extreme climate occurrences. Crop growth condition models can be utilized with time series of spatially explicit information from satellite remote sensing (RS) [5] [6].

Due to its capacity to automatically uncover patterns and representations from enormous datasets, deep learning, a branch of machine learning, has attracted considerable interest in a number of fields [7]. Deep learning algorithms can analyze enormous volumes of spatial and temporal data when paired with satellite imagery to produce valuable insights about crop development and yield potential. The development of crops is influenced by a variety of climatic conditions, including temperature, precipitation, and vegetation indices, which are all depicted in satellite imagery. The appropriateness of several neural network models, such as artificial neural networks (ANN) and deep neural networks (DNN), and machine learning (ML) models, such as random forests (RF), support vector machines (SVM), has been examined in a number of studies for yield estimation [7] [8].

Deep learning models combined with satellite imagery provide significant advantages over conventional approaches. First, it allows for the investigation of huge agricultural fields that span wide geographic areas. It also offers to monitor of cr

growth and health in close to real-time, enabling prompt interventions and efficient resource use. Furthermore, it

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lessens the need for labour-intensive field surveys, which decreases the time and expense of data collecting. [7] [9] [10]

Satellite imagery from Earth observation satellites with multispectral sensors, like Landsat, Sentinel, or MODIS, is obtained in order to develop a deep learning-based agricultural yield estimation system. As a historical record of crop growth phases and climatic circumstances, these sensors periodically take pictures. Pre-processing operations are performed on the obtained imagery to correct atmospheric effects, normalize radiometric values, and time-align images.

Then, for estimating agricultural yield, deep learning models such as recurrent neural networks (RNNs), and convolutional neural networks (CNNs) and their combinations are used. While RNNs can effectively capture temporal correlations in crop development patterns, CNNs are effective at extracting spatial characteristics from satellite pictures. With the use of transfer learning approaches, pre-trained models may be applied to massive image datasets, improving generalization and speeding up training.

Crop yield data is gathered from field surveys or remote sensing data and used to train the algorithms on labelled datasets. The models develop the ability to extract important elements from satellite pictures, including data on texture, colour, and vegetation indices. To increase prediction accuracy, further elements can be added, such as meteorological information, information about the soil, and information about previous crop yields.

Once trained, the deep learning model can be used to forecast crop yields based on fresh, previously unobserved satellite pictures. The model's outputs provide estimates for a range of geographical scales, from small fields to large regions or the entire world. To validate and assess the model, these projections can be compared to actual yield data gathered through physical crop sampling or yield reporting systems.

Using deep learning and satellite data to estimate crop yields has the potential to completely transform agricultural methods. It helps decision-making processes for insurance and commodity trading and enables precision agriculture techniques, resource allocation that is optimal, and crop health monitoring. However, issues like the scarcity of labelled training data, the impact of cloud cover on the quality of satellite images, and the requirement for substantial computer resources for deep learning model training need to be addressed.

In summary, combining deep learning methods with satellite images offers a potent method for precise and fast agricultural production estimation. This strategy has the potential to increase agricultural output, optimize resource management, and contribute to global food security by utilizing the strengths of deep learning algorithms and the quantity of data offered by satellite photography. For this technology to be used to its full potential and be applied to the production of food that is both sustainable and effective, it is essential that research and development in this area continue.

2. Literature Survey:

Recent years have seen a substantial increase in interest in crop yield estimation using deep learning and satellite photography. Research has shown that deep learning algorithms, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are useful at forecasting crop yields with high accuracy. These models can extract spatial and temporal features, including trends related to crop development and environmental conditions, by utilizing satellite imagery and auxiliary data.

Deep learning and satellite images have been combined, and the results have been encouraging, outperforming more conventional techniques in terms of accuracy. By delivering accurate and fast crop output predictions and assisting in resource management and decision-making, this method has the potential to change agricultural operations. Remote sensing data were translated into histograms of pixel intensities during data pre-processing, and these histograms served as the models' input. Three cutting-edge models include random forest [18], Before a convolutional neural network (Conv3D) and CNN, long-short-term memory (LSTM) is employed. Because the 2D does not account for the temporal signal, 3D convolutions were used to make it possible to learn the temporal information [19].

Accurate and reliable data collection is a crucial first step in putting into reality a deep learning and satellite imagery-based agricultural production estimation system. Data collection comprises obtaining satellite imagery, ground-based yield data, and applicable auxiliary data. This section describes the key components of data collection for predicting agricultural yield. On the other hand, the CNN-LSTM model combines LSTM with 2-Dimensional Convolutional neural networks. The effectiveness of characterizing temporal patterns at various frequencies is considerably improved by LSTM by bridging big time gaps between inputs over varying time intervals [20] Rectified Linear Units, or ReLU, were chosen as the activation function. A dropout layer with a dropout probability of 0.5 was present in both models. The Tensor Flow library was used to implement Python deep neural networks [21].

1. Satellite Imagery:

Earth observation satellites equipped with multispectral sensors, such as Landsat, Sentinel, or MODIS, provide valuable satellite imagery for crop monitoring. These sensors capture images at regular intervals, offering a historical record of crop growth stages and environmental conditions. The satellite imagery should be obtained at suitable spatial and temporal resolutions to capture the desired level of detail for crop yield estimation. Data from 2008 to 2019 for Land Surface Temperature (MOD11A1), Evapotranspiration (ET) (MOD16A2), and Surface Reflectance (MOD09A1) based on MODIS were utilized for the county-level study. The information on the data obtained by satellite is shown in Figure 1.

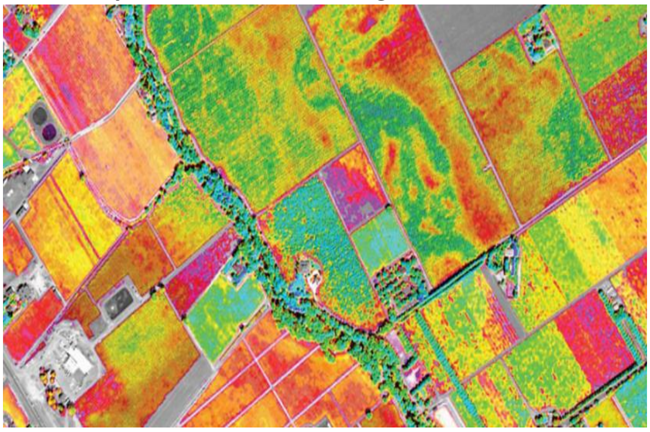
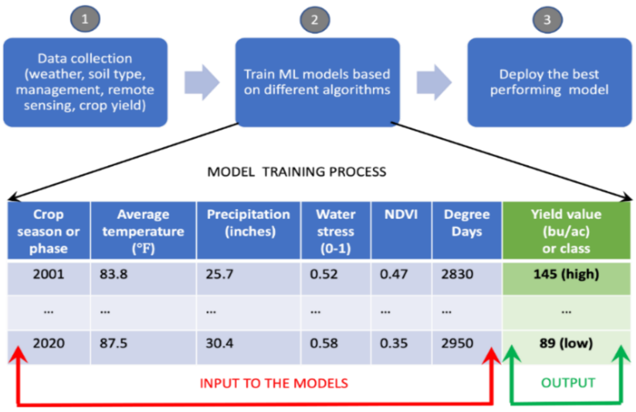


Fig 1- Satellite image of the field

2. Auxiliary Data:

In addition to satellite imagery and ground truth yield data, auxiliary data can provide valuable contextual information for crop yield estimation. This data may include weather data (such as temperature and rainfall), soil characteristics (such as soil moisture and composition), crop management techniques (such as irrigation and fertilizer), and historical crop yield records. Incorporating auxiliary data enhances the predictive capabilities of the deep learning models by capturing additional factors that influence crop growth and yield potential. Only observations made between April and September were taken into account because this is when maize and soybeans are typically grown [14]. Using Google Earth Engine, the time series were accessed, prepared for export, and exported [15]. An illustration of the type of data gathered by satellites is shown in Figure 2.



Crop season or phase	Average temperature (°F)	Precipitation (inches)	Water stress (0-1)	NDVI	Degree Days	Yield value (bu/ac) or class
2001	83.8	25.7	0.52	0.47	2830	145 (high)
...	...	...	...	...	...	...
2020	87.5	30.4	0.58	0.35	2950	89 (low)

Fig 2 – tabular data collected from the satellite.

3. Data Pre-processing:

Before training the deep learning models, the acquired data needs to undergo pre-processing steps to ensure consistency and compatibility. Satellite imagery may require pre-processing steps such as radiometric calibration, atmospheric correction, and image registration to correct for artefacts and align the images in a common spatial reference frame. Ground truth yield data may need to be standardized or normalized to remove any biases or inconsistencies. Used as labelled data for training and validation at the county level by the National Agricultural Statistics Service of the United States Department of Agriculture [16]. Figure 3 describes the process of data processing of crop yielding.

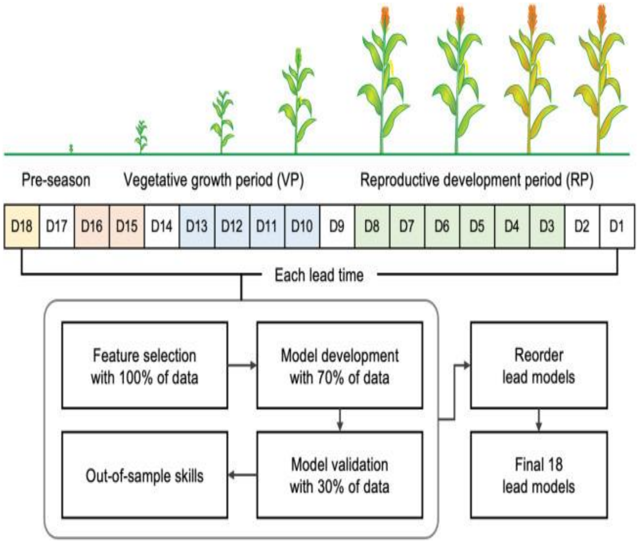


Fig 3 – data processing from seeding to crop yielding

4. Ground Truth Yield Data:

Ground truth yield data serves as the reference data for training and validating the deep learning models. It is collected through field surveys or remote sensing techniques, such as crop sampling or yield reporting systems. Field surveys involve physically measuring and recording crop yields in representative sample areas. The Harmonized Landsat Sentinel-2 (HLS) product [17] supplied a Level-2 Nadir BRDF (Bidirectional Reflectance Distribution Function)-Adjusted surface Reflectance (NBAR) at a 30 m spatial resolution for the field-level analysis. The ground truth data should cover a sufficient number of fields to ensure representative sampling and capture the variability within the target region. Figure-4 is a map of the ground survey done in the year 2007 to make sure is suitable for crop yielding or not.

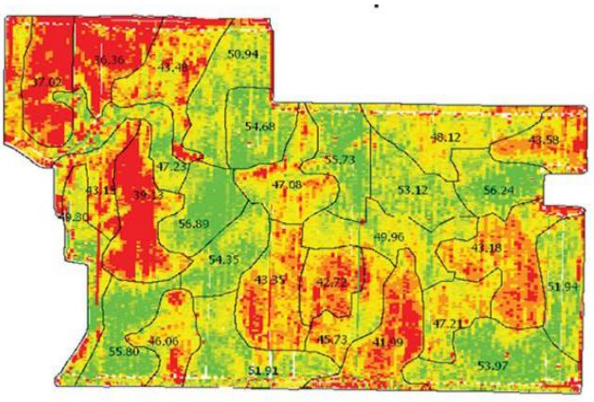


Fig 4 – Survey of ground

5. Data Integration:

To train the deep learning models, satellite imagery, ground truth yield data, and auxiliary data need to be integrated. This integration involves spatially and temporally aligning the data sources and associating the corresponding yield information with the satellite imagery at specific locations and time points. Integration techniques may vary depending on the specific dataset and crop yield estimation system requirements. For the field-level analysis, yields from fields in four counties in Iowa were gathered by machines.[23] These data were filtered to exclude outliers and headlands, or yields that deviated by more than three standard deviations. The locations where soy and maize are grown were hidden using annual Cropland Data Layer (CDL) maps. When masking MODIS and HLS observations for comparable growing seasons, only pixels with maize or soybeans were selected [7]. How the data is calibrated and tested for usage in the future is shown in Figure 5.

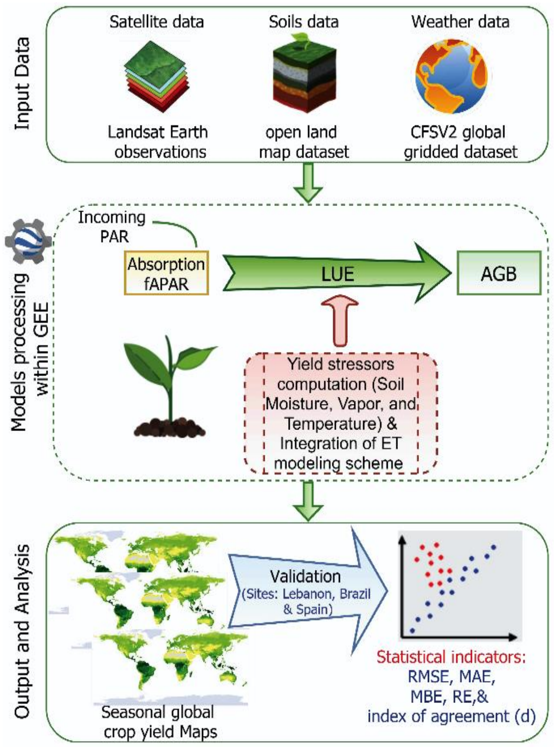


Fig 5 – Trained and test data

For precise and dependable agricultural yield estimation utilizing deep learning and satellite imagery, high-quality data collection is required. The choice of satellite images, the creation of ground truth data gathering techniques, and the inclusion of pertinent auxiliary data should all be carefully taken into account. Crop yield estimates are more accurate when data has been properly pre-processed and integrated, making it appropriate for deep learning model training and validation.[22]

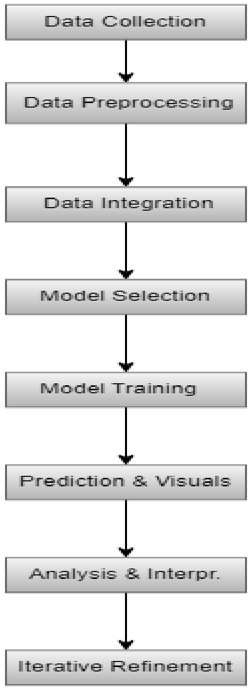


Fig 6:- block diagram of literature survey

3. Proposed Methodology:

The rate at which crops can be harvested in a specific area depends on a number of factors. To estimate agricultural output, a variety of machine learning techniques can be used. The deep learning technique is the only one of these prediction technologies that has not yet been applied. Illustrates the approach suggested to boost crop productivity based on optimization-based decision-making. In this case, gathering the initial dataset and then pre-processing it to normalize the Z-score will gradually purge the data of unwanted flaws. After that, the features from the pre-processed data were extracted using an adaptive shearlet technique. Tweak Chick Swarm Optimization (TCSO)-based feature selection was the method used to find the specialized features. Discrete hybrid Deep belief networks with VGG NET classifiers were used to efficiently rank and categorize the crops based on yield. Information on the crop is displayed in the following table.

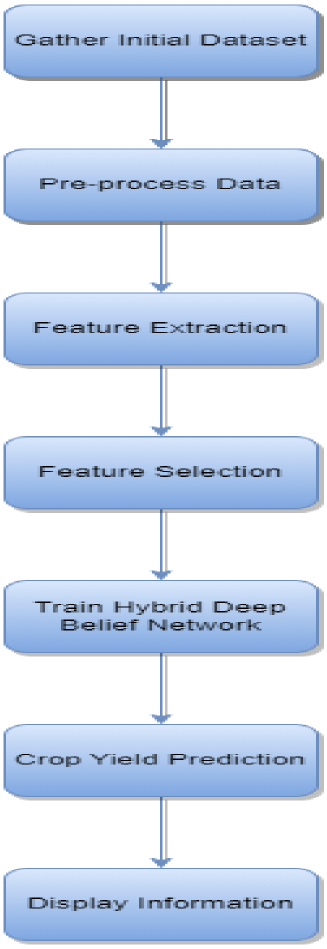


Fig 7: - flow chart of the VGG methodology

Following are the steps with description of the Visual Geometry Group (VGG) method:

1. Gather Initial Dataset:

Gather information on crop productivity, taking into account elements including crop type, farming methods, weather, and harvest yields. The analysis's starting point will be this dataset.

2. Pre-process Data:

Pre-processed and clean the dataset to eliminate any unwanted or inconsistencies flaws. Apply techniques such as data normalization using Z- scores to standardize the data and make it more ease and suitable for analysis.

3. Feature Extraction:

Apply an adaptive shearlet approach on the pre-processed dataset to extract the necessary features. This method makes it possible to identify specialised traits that are crucial for estimating crop productivity.

4. Feature Selection:

For feature selection, use the Tweak Chick Swarm Optimisation (TCSO) algorithm. TCSO is a decision-making technique based on optimisation that aids in locating the most valuable and significant features for forecasting crop yield.

5. Train Hybrid Deep Belief Networks:

Use DBNs (Discrete Hybrid Deep Belief Networks) in combination with classifiers from VGG NET. Train DBNs with the chosen attributes to quickly rank and classify crops according to projected yield.

6. Crop Yield Prediction:

Using the chosen characteristics and classification models, use the trained DBNs to forecast crop yields. The models must to be able to offer precise predictions of crop productivity for various crops in a specific region.

7. Display Information:

Give the facts on the anticipated crop yield in a manner that makes sense, such table or dashboard. Details like crop kind, expected yield, and any other pertinent information may be included in the table.

4. Results:

Following is the Gathered data from the satellite imagery of the agricultural fields where the crops are being cultivated. This satellite imagery will serve as the input for the deep learning model.

Crop	Minimum capital	Rank	Flexible Marketing	Rank	R(f1) – R(f2)	(R(f1)-R(f2))^2
Rice	4	4	5	3	1	1
Millet	6	2	7	1	1	1
Pulses	5	3	6	2	1	1
Maize	7	1	6	2	-1	1

TABLE 1: - CALCULATING THE BEST CROP RELATED TO ITS RANK

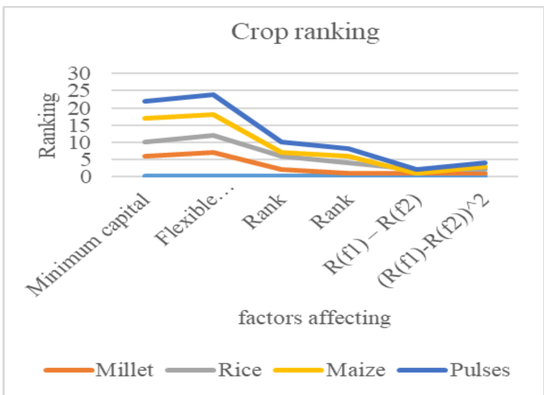


Fig 8: - CROP RANKING

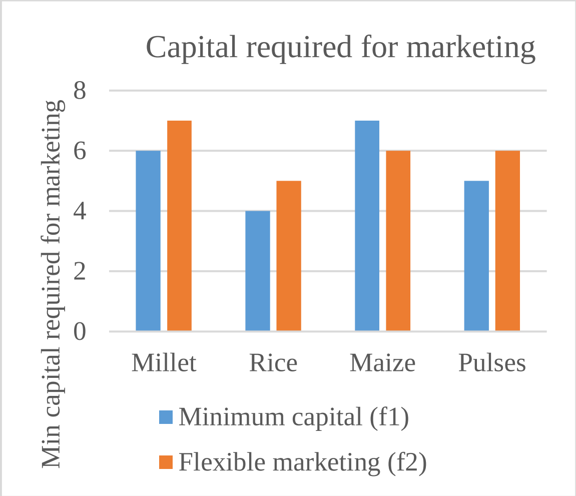


Fig 9: - Minimum capital required for marketing

Based on the provided table with crop rankings, minimum capital, flexible marketing, and R(f1) - R(f2) values, we can calculate the results as follows:

- Minimum Capital (f1): This represents the minimum capital required for each crop. In this data, Maize has the highest minimum capital requirement of 7, suggesting it requires the most significant investment among the crops.
- Flexible Marketing (f2): Indicates the flexible marketing rank for each crop. A higher rank implies more flexibility. In this data, Millet and Rice both have a flexible marketing rank of 7, indicating they are considered the most flexible crops for marketing.
- Rank (f1) and Rank (f2): These columns represent the rankings assigned to each crop for minimum capital and flexible marketing, respectively. For example, in this data, Maize is ranked 1 for minimum capital, indicating it has the lowest capital requirement. Millet and Rice are both ranked 1 for flexible marketing, suggesting they are the top choices in terms of marketing flexibility.
- R(f1) - R(f2): The difference between the ranks for flexible marketing and minimum capital is shown in this column (Rank (f1) - Rank (f2). It conveys a preference for higher rankings in terms of capital needs. A desire for a lower capital requirement is indicated by positive values, whilst a preference for a greater capital demand is indicated by negative values.
- (R(f1) - R(f2))^2: This column represents the squared value of the difference between the rankings. It allows for a comparison of the magnitudes of differences and can help in measuring the relative significance of the preferences.
- Overall, based on the provided data, Millet and Rice have the highest rankings for flexible marketing and relatively low capital requirements. Maize, on the other hand, has the highest minimum capital requirement and ranks lower for flexible marketing. Pulses also have a relatively low capital requirement and rank high for flexible marketing.

These results provide insights into the rankings, capital requirements, and flexible marketing of different crops, allowing stakeholders to make informed decisions based on their preferences and resource constraints.

5. Discussion

Based on the results of the provided data, let's discuss some key points:

In the agricultural sector, Millet and Rice rank highest for flexible marketing, indicating their versatility and adaptability in marketing strategies. This presents an opportunity for stakeholders to explore various channels and approaches to maximize market potential. On the other hand, Maize requires the highest minimum capital investment, underscoring the financial considerations associated with cultivating this crop. This information is crucial for budgeting, resource allocation, and risk management. Moreover, the positive values in the R(f1) - R(f2) column demonstrate a preference for lower minimum capital requirements, reflecting stakeholders' inclination towards crops with lower capital demands. Understanding this preference can inform investment decisions and resource allocation strategies. Interestingly, the R(f1) - R(f2) values for all crops indicate a balanced or neutral preference for marketing flexibility, suggesting that stakeholders do not strongly favour crops with either higher or lower marketing flexibility. It emphasizes the importance of considering other factors such as market demand, pricing, and competition in determining marketing strategies. The (R(f1) - R(f2))^2 values, representing the magnitudes of differences in preferences, suggest that minimum capital and marketing flexibility have similar importance across the crops. Strategic crop selection could prioritize crops like Millet and Rice, which offer high marketing flexibility and relatively lower capital requirements. This favourable positioning aligns with both marketing and financial considerations. The results also reveal diversification opportunities, as each crop possesses unique strengths in terms of capital requirements and marketing flexibility. This encourages stakeholders to diversify their crop portfolios, mitigating risks and capitalizing on market conditions. Lastly, further investigation into market trends, consumer preferences, and input costs is recommended to enhance decision-making and develop more informed strategies in crop selection, investment planning, and marketing efforts.

6. Conclusion

In order to accurately anticipate crop yields throughout the entire dataset, this paper developed a deep learning-based approach that made use of environmental data and management strategies. In order to categorize crops according to the planting schedule, we employ a discrete hybrid deep belief network with the VGG NET technique. With the provided strategy, three separate datasets can be employed. It might be possible to enhance crop separation in timelines based on planting by focusing on a theoretical model in this application. In comparison to three other previously published techniques, the effectiveness of the applied strategy is assessed. The proposed strategy outperforms earlier methods in terms of performance. It is obvious in this case that the suggested technique picks the crop with the greatest chance of financial success.

References

[1] M. van der Velde et al., "In-season performance of European Union wheat forecasts during extreme impacts," Sci Rep, vol. 8, no. 1, pp. 1–10, Oct. 2018, doi: 10.1038/s41598-018- 33688-1.

[2] H. Jiang et al., "A deep learning approach to conflating heterogeneous geospatial data for corn yield estimation: A case study of the US Corn Belt at the county level," Global Change Biology, vol. n/a, no. n/a, doi: 10.1111/gcb.14885.

[3] F. Gao, M. Anderson, C. Daughtry, and D. Johnson, "Assessing the Variability of Corn and Soybean Yields in Central Iowa Using High Spatiotemporal Resolution MultiSatellite Imagery," Remote Sensing, vol. 10, no. 9, p. 1489, Sep. 2018, doi: 10.3390/rs10091489.

[4] F. Kogan et al., "Winter wheat yield forecasting in Ukraine based on Earth observation, meteorological data and biophysical models," International Journal of Applied Earth Observation and Geoinformation, vol. 23, pp. 192–203, Aug. 2013, doi: 10.1016/j.jag.2013.01.002.

[5] J. Liu et al., "Crop Yield Estimation Using Time-Series MODIS Data and the Effects of Cropland Masks in Ontario, Canada," Remote Sensing, vol. 11, no. 20, p. 2419, Jan. 2019, doi 10.3390/rs11202419.

[6] F. Novelli, H. Spiegel, T. Sandén, and F. Vuolo, "Assimilation of Sentinel-2 Leaf Area Index Data into a Physically-Based Crop Growth Model for Yield Estimation," Agronomy, vol. 9, no. 5, p. 255, May 2019, doi 10.3390/agronomy9050255.

[7] N. Kim, K.-J. Ha, N.-W. Park, J. Cho, S. Hong, and Y.-W. Lee, "A Comparison Between Major Artificial Intelligence Models for Crop Yield Prediction: Case Study of the Midwestern United States, 2006–2015," ISPRS International Journal of Geo-Information, vol. 8, no. 5, p. 240, May 2019, doi: 10.3390/ijgi8050240.

[8] J. Richetti et al., "Using phenology-based enhanced vegetation index and machine learning for soybean yield estimation in Paraná State, Brazil," JARS, JARSC4, vol. 12, no. 2, p. 026029, Jun. 2018, doi: 10.1117/1.JRS.12.026029.

[9] D. M. Johnson, "An assessment of pre- and within-season remotely sensed variables for forecasting corn and soybean yields in the United States," Remote Sensing of Environment, vol. 141, pp. 116–128, Feb. 2014, doi: 10.1016/j.rse.2013.10.027.

[10] S. Khaki and L. Wang, "Crop Yield Prediction Using Deep Neural Networks," Front. Plant Sci., vol. 10, 2019, doi: 10.3389/fpls.2019.00621.

[11] E. Vermote, "MOD09Q1 MODIS/Terra Surface Reflectance 8-Day L3 Global 250m SIN Grid V006." NASA EOSDIS Land Processes DAAC, 2015, doi: 10.5067/MODIS/MOD09Q1.006.

[12] Z. Wan, S. Hook, and G. Hulley, "MOD11A1 MODIS/Terra Land Surface Temperature/Emissivity Daily L3 Global 1km SIN Grid V006." 2015, [Online]. Available: https://doi.org/10.5067/MODIS/MOD11A1.006.

[13] S. Running, Q. Mu, and M. Zhao, "MOD16A2 MODIS/Terra Net Evapotranspiration 8-Day L4 Global 500m SIN Grid V006." 2017, [Online]. Available: https://doi.org/10.5067/MODIS/MOD16A2.006.

[14] T. Sakamoto, B. D. Wardlow, A. A. Gitelson, S. B. Verma, A. E. Suyker, and T. J. Arkebauer, "A Two-Step Filtering approach for detecting maize and soybean phenology with time-series MODIS data," Remote Sensing of Environment, vol. 114, no. 10, pp. 2146–2159, Oct. 2010, doi 10.1016/j.rse.2010.04.019.

[15] N. Gorelick, M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore, "Google Earth Engine: Planetary-scale geospatial analysis for everyone," Remote Sensing of Environment, 2017, doi: 10.1016/j.rse.2017.06.031.

[16] "USDA/NASS QuickStats Ad-hoc Query Tool." https://quickstats.nass.usda.gov/ (accessed Jan. 08, 2020).

[17] M. Claverie et al., "The Harmonized Landsat and Sentinel-2 surface reflectance data set," Remote Sensing of Environment, vol. 219, pp. 145–161, Dec. 2018, doi: 10.1016/j.rse.2018.09.002.

[18] L. Breiman, "Random Forests," Machine Learning, vol. 45, no. 1, pp. 5–32, Oct. 2001, doi: 10.1023/A:1010933404324.

[19] C. Pelletier, G. I. Webb, and F. Petitjean, "Temporal Convolutional Neural Network for the Classification of Satellite Image Time Series," Remote Sensing, vol. 11, no. 5, p. 523, Jan. 2019, doi: 10.3390/rs11050523.

[20] S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” Neural Computation, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

[21] M. Abadi et al., “TensorFlow: A System for Large-Scale Machine Learning,” 2016, pp. 265–283, Accessed: Jan. 10, 2020. [Online]. Available: https://www.usenix.org/conference/osdi16/technicalsessions/presentation/abadi.

[22] Dange, B. J. ., Mishra, P. K. ., Metre, K. V. ., Gore, S. ., Kurkute, S. L. ., Khodke, H. E. . and Gore, S. . (2023) “Grape Vision: A CNN-Based System for Yield Component Analysis of Grape Clusters ”, International Journal of Intelligent Systems and Applications in Engineering, 11(9s), pp. 239–244. Available: https://ijisae.org/index.php/IJISAE/article/view/3113.

[23] Gore, S. ., Dutt, I. ., Dahake, R. P. ., Khodke, H. E. ., Kurkute, S. L. ., Dange, B. J. . and Gore, S. . (2023) “Innovations in Smart City Water Supply Systems ”, International Journal of Intelligent Systems and Applications in Engineering, 11(9s), pp. 277–281. Available at: https://ijisae.org/index.php/IJISAE/article/view/3118.

[24] Tholkapiyan, M. ., Ramadass, S. ., Seetha, J. ., Ravuri, A. ., Vidyullatha, P. ., Shankar S., S. . and Gore, S. . (2023) “Examining the Impacts of Climate Variability on Agricultural Phenology: A Comprehensive Approach Integrating Geoinformatics, Satellite Agrometeorology, and Artificial Intelligence”, International Journal of Intelligent Systems and Applications in Engineering, 11(6s), pp. 592–598. Available at: https://ijisae.org/index.php/IJISAE/article/view/2891.

[25] Rajesh Kumar Chaudhary, M. K. C. (2021). The Role of School Management Towards Staff Motivation for Effective Performance in Nepal: During the Covid-19. International Journal of New Practices in Management and Engineering, 10(01), 01–11. https://doi.org/10.17762/ijnpme.v10i01.93

[26] Sherje, D. N. . (2021). Thermal Property Investigation in Nanolubricants via Nano- Scaled Particle Addition. International Journal of New Practices in Management and Engineering, 10(01), 12–15. https://doi.org/10.17762/ijnpme.v10i01.96