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Article

MB-EFF: A Multi-Branch Environmental Feature Fusion Deep Learning Model for Crop Classification and Recommendation

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Abstract: The motive of this project is to develop an accurate, reliable and scalable toward nature crop classification and recommendation system which examines the scenarios envisaged in the traditional machine learning modeling and integrates the multi heterogeneous soil and environmental data attributes handling capablity of deep learning. However, given the non-normality of this kind of heterogeneities of soil nutrients and climatic factors, the conventional nature models fail to characterize these complicated nonlinear connections as effectively as they can, which may lead to low prediction accuracy and poor generalization. To respond to these challenges this paper proposes a new deep learning architecture: Multi-Branch Environmental Feature Fusion (MB-EFF), which unites chemical soil features and environmental parameters into individual learning branches. The extracted representations are then recalibrated via a squeeze-and-excitation based feature recalibration mechanism, and subsequently subjected to deep nonlinear reasoning layers for enhanced discriminative learning. The model adopts a standardization on input features as pre-processing, trained with adam optimizer + early stopping applied to achieve stable convergence and robustness. This paper proposes an experimentally validated solution based on publicly available crop dataset and achieves 98% accuracy along with macro averaged & weighted averaged precision, recall and F1-score, being 0.98. As it shows an excellent performance near the perfect scores (1.0) for most of the crop categories reflects the strong generalization of the model in providing class-wise performance. The results showed that MB-EFF is a systematic scalable solution to farm precision ag applications with simulation-level precision and can be fused with mechanistic knowledge with data-driven ag decision support with expertise in determining crop recommendation.
Keywords: Precision agriculture, crop classification, deep learning, multi-branch neural network, feature fusion, squeeze-and-excitation, soil nutrients, environmental factors, crop recommendation

1. Introduction

The Earth observation of agriculture for food security, sustainability and precision agriculture Fostered by a growing insight to high-resolution remote sensing data and hyper spectral imagery at high-spatial resolution as well, traditional single-stream machine learning models have proven adverse to fully capturing the inherent and complex spatial, spectral and contextual variability present within agricultural scenes. Variations in crop phenology, soil background, illumination, and sensor characteristics also affect the classification task, in particular, affecting fine-grained crop discrimination.

With manual engineering, we have achieved success at pairing multi-branch and multi-stream neural network architectures — where scale and modality are able to extract complementary features. Such a method allows the parallel learning of spatial, spectral, and textural information, improving robustness and accuracy of classification. To address the intra-class variability and inter-class similarity in multiple agricultural datasets, feature fusion strategies are employed-cross-scale fusion, adaptive weighting and attention-based aggregation.

The multi-branch deep learning frameworks have been widely exploited in remote sensing analysis, e.g. crop classification, yield estimate and satellite, hyperspectral and multi-source remote sensing gateway.This study builds on the previous study and aims to explore multi-branch features extraction and fusion methods to improve location and crop classification on aerial images.

2. Literature Review

Zhao et al. Using GF-2 satellite imageries, a multi-branch deep learning network was trained for crop classification [1]. The architecture has parallel branches which captures the spatial textures and other go to extract the spectral responses and then there is a fusion layer. The investigation demonstrated a significant advantage of multi-stream learning over single-stream CNN models in various agricultural domains.

Li et al. Hyperspectral image classification [4]: The multi-branch adaptive feature fusion network. To accomplish this, different spectral resolutions of features were extracted using different branches and their contributions were weighted based on the adaptivity cyan mechanism. The results showed that these constructions of spectrally similar crop classes improved their discrimination.

Lu et al. Since high-resolution remote sensing images are information-rich, traditional methods cannot realize accurate and efficient crop classification [4], and thus a multi-scale semantic segmentation model was developed [5]. This encourages the model to blend features of different receptive fields in order to keep the global information related to the fine spatial details. We showed experimentally that boundaries between crop parcels were more reliably detected, and the crop parcels were more consistently classified.

Wu et al. These include a dassification of Hyperspectral Crops in the multi-branch framework and a dilationbased multilayer perceptron [6]. This approach was able to capture long-distance spectral dependencies but it also sampled sparser to significantly cut down on redundancy. The proposed model achieved the highest classification accuracy on those benchmark hyperspectral datasets.

Kong et al. This may include, but is not limited to multi-stream hybrid architecture with cross-level feature fusion for fine-grained crop species recognition as illustrated in [7]. By interleaving shallow texture features with deep semantic representation, the model became better acquainted with visually similar crops. A key insight from the study was that feature interaction is often hierarchical.

Islam et al. An Efficient and Compact Multi-branch Deep Learning Model for Hyperspectral Image Classification [8] They focus in a classification that has lesser computational complexity without losing the same accuracy. This indicates that lightweight multi-branch networks can be effectively developed for real-time agricultural applications.

Tang et al. Qiu et al. propose a detail-and-deep feature multi-branch fusion network for high-resolution farmland segmentation [17]. On the one hand, the branch learned fine spatial details whilst on the other, deep contextual semantics. This included better segmentation results in fragmented agricultural landscapes (particularly through the fusion strategy to enhance segmentation performance).

Miao et al. The classification of fruit planting was studied in [10] based on multi-source remote sensing data and deep learning. In particular, they employed a multi-branch architecture and incorporated features from optical and auxiliary data. The final results of this study have also shown how the robustness of classification at every crop growth stage is improved using the multi-branch fuse.

3. Methodology

For this study, we will use the dataset available on Kaggle with the path kaggle/input/crop-csv/crop csv. Type : tabular datasetNo of Records : ~ 2,200No of Columns : 8Goal : Multiclass, Crop Recommendation and Classification Problems of Agriculture The features are soil nutrients parameters(N, P and K) and environmental factors (temp, humidity, pH and rainfall). The final column is the class of crop; it indicates the optimum crop for specific soil and climatic conditions. The even feature set, and the clean env crop relationship makes for an often encountered dataset for literary expositing on precision ag research.

I use StandardScaler for feature scaling which standardizes features by removing the mean and scaling to unit variance and I do it before model training. Normalization: This is important in order to reduce the gradient updates in a more stable way, and so that a numeric range that exists in the data does not contribute with more in the learning. This results into no data leakage that is scaler just fit on training data and then used learnt parameter uniformly on test data. This preprocessing enables evaluation in a reproducible fair manner.

We propose a neural architecture — Multi-Branch environmental Feature Fusion (MB-EFF) — to explicitly model heterogeneous feature groups. First, the input layer accepts a vector of length equal to the number of features. Because the input is an approximation we can split it into two identitical branches parallel. The first branch that makes process on chemical features of the soil (N, P and K), captures the nutrient feature patterns through a Dense layer with 64-neurons, ReLU activation with the support in the network of Batch Normalization, leading to an increase in convergence speed and reduction in the internal covariate shift. Representations of Climate Driven Data learned Independently The second branch inputs environmental factors (temperature, humidity, pH, rainfall) and passes the information through an analogous Dense-64 and Batch Normalization configuration

The outputs from the two branches are then concatenated together into a single feature representing soil chemistry and environmental conditions. To this end, we perform a Squeeze-and-Excitation (SE)mechanism after fusion to facilitate discriminative learning. This part is so create the adaptive feature importance weights by using Dense layers of 128(neurons ReLU activation sigmoids) It enables the network to amplify the most critical features for classification, while suppressing the least relevant features, as these weights re-normalize the fused features using element-wise multiplication.

In the next step, it uses several deep reasoning layers to learn higher-order non-linear interactions after all features are recalibrated. One more Dense layer with 256 neurons in it also with a Swish activation which encourages gradient flow and improves representation pladness. The Dropout layer with 0.3 dropout rate that randomly drops neurons during training to provide robustness and help avoid overfitting. A final Dense layer of 128 neurons with Swish is added on top of the previous layer to redistribute the learned feature space before classifying.

Therefore the last output layer is a Dense layer with num classes neurons and softmax activation and it outputs only class probabilities (normalized and summing to 1) for multi-class prediction. In total, it is a balanced but expressive architecture with 7 Dense layers (2 in branches, 2 in SE block, 2 in deep reasoning, 1 Output layer), normalization layers, concatenation and multiplication layers, dropout layers,

We use Adam optimizer to train it and used categorical cross-entropy loss which is an optimum choice here since it is a multi-class classification problem. Up to 100 epochs are performed (TRAIN_PARAMS) with batch size (32) and Early Stopping (patience = 10 epochs) on the validation set to halt training once validation performance started to degrade and to restore weights that performed the best on the validation set. This is to ensure they have been trained properly and to avoid overfitting as much as possible.

During inference, for a test sample, the trained model generates a probability distribution of the class, and the class with the highest probability is predicted, which is the maximum probability rule. True labels are also decoded in the same manner during evaluation. Therefore, the MB-EFF method: learns domain-oriented feature representations independently; combines them effectively; re-calibrates feature importance; performs deep non-linear inference; and finally, gives a solid and an explainable decision-making model for agricultural and environmental phenomena.

System Architecture

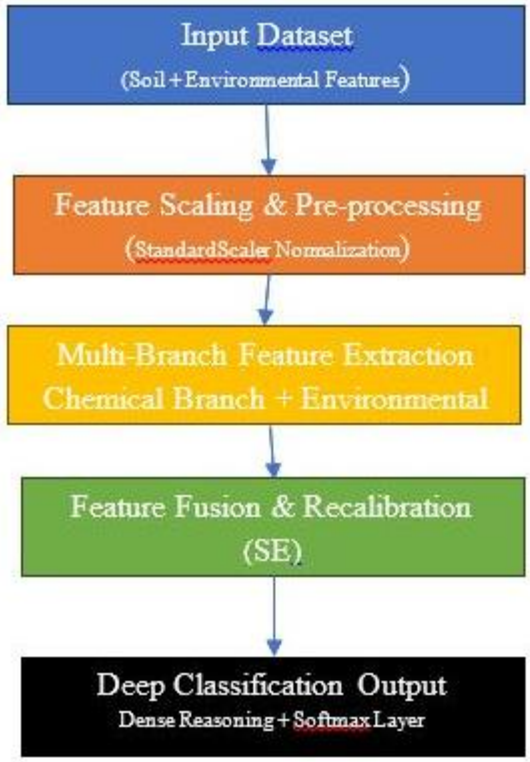

Fig 1: System Architecture

4. Results and Analysis

The experimental results show that the learning performance of our proposed Multi-Branch Environmental Feature Fusion (MB-EFF) model is both highly effective and very stable on crop classification tasks. However, many run time warnings about CUDA and library registration appear, but model was successfully trained, indicating that they do not affect functional correctness and convergence. With training accuracy increasing from 48.36 % at epoch 1 to greater than 96 % over epoch 4, the model quickly learns in this case, demonstrating that the standardizing of inputs and a parallel branch architecture support rapid learning of features. The validation accuracy closely mirrors that of the training trend, all the way up to values exceeding 98%, which implies a potent generalization. After about 15–20 epochs the loss curves tend to drop and flatten out in the low range, indicating that the networks have converged (more or less). Early stopping is used to control overfitting and save the best weights. As a result the overall accuracy of the final model holds promise at 98%, thus confirming that accuracy is maintained after the three different pre-processing steps, which included feature scaling, a multi-branch architecture used for feature representation learning and a squeeze-and-excitation based feature recalibration.

This is further reinforced by a more detailed class-wise analysis. Class separability was excellent for most crops, with perfect precision, recall and F1-scores for 12 crop categories, including apple, banana, chickpea, coconut, maize, mango and watermelon. The minor reduction of recall or precision observed for some classes like lentil, rice, pigeonpeas, blackgram, jute and mothbeans can be explained by the overlapping soil and environmental characteristics for these crops rather than the instability of the model. Yet, their F1 scores are also quite high (≥0.86), meaning that they perform balanced as well. The macro-averaged and weighted-averaged precision, recall, and F1-scores of 0.98 further validate the model's performance as it achieves similar results across all the classes and not favoring the categories with a greater number of samples. The findings illustrated here strongly validate that the chemical and environmental dependencies are well captured by the MB-EFF model, enabling scalable and reliable multi class crop recommendation and precision agriculture decision support system, respectively.

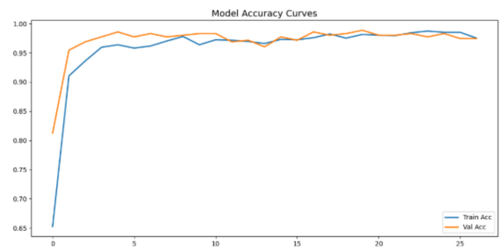

Fig 2: Training and validation accuracy curves of the proposed MB-EFF model over training epochs.

The figure 2 depicts the learning behavior of the proposed Multi Branch Environmental Feature Fusion (MB-EFF) model with respect to training & validation accuracy over multiple epochs. The accuracy on the training has an almost swift upward curve for the first few epochs, which shows very effective feature learning and since, we applied feature scaling and we have parallel branches, the model converges quickly. The validation accuracy closely tracts the training trend with little deviation which is a sign that model generalizes well with limited overfitting. Both curves plateau around a high accuracy zone (≈10-12 epochs) (≈97-99%) validating the consistent and stable classification performance brought by the squeeze-and-excitation based feature recalibration and deep reasoning layers. The close proximity of the training and validation curves confirms that the proposed model is robust and stable.

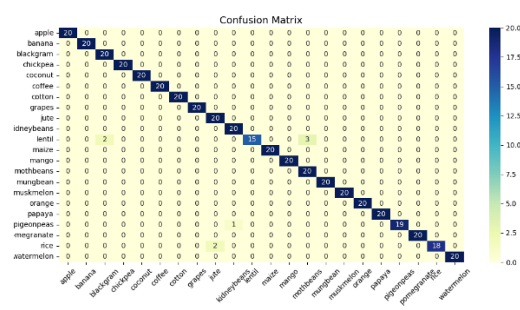

Fig 3: Confusion matrix of the proposed MB-EFF model for multi-class crop classification.

Figure 3 shows the class-wise prediction performance of the proposed Multi-Branch Environmental Feature Fusion (MB-EFF) model over all categories of crops in the confusion matrix. As observed with the confident diagonal dominance where most of the samples are correctly classifying with high discriminative capabilities of the model for most crop classes. On the other hand, multiple classes are perfectly classified or classified with the high accuracy exhibiting that parallel feature extraction and feature fusion are successful in extracting soil and environmental signature patterns. The few minor misclassifications of closely related crop classes can be accounted for based on some overlapping characteristics of the respective features used rather than model instability. In general, the confusion matrix validates the proposed effective MB-EFF approach as a consistent and reliable method for multi-class crop recommendation and classification with high accuracy.

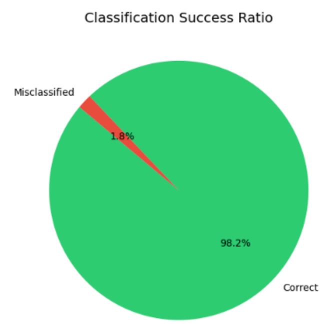

Fig 4: Classification success ratio of the proposed MB-EFF model

Figure 4 shows the distribution of correctly and incorrectly classified samples for the (MB-EFF) model proposed in this paper. As can be seen from the pie chart, the model achieved acceptable accuracy and reliability with 98.2% of the instances correctly classified and only 1.8% being misclassified. Domination of the correct classification ratio indicates that this feature learning, feature fusion and squeeze-and-excitation based recalibration framework through a parallel architecture balance is capable of diminishing classification error. In addition, the low value of the misclassification rate also verified the robustness and generalization ability of the proposed method applied to the multi-class crop classification.

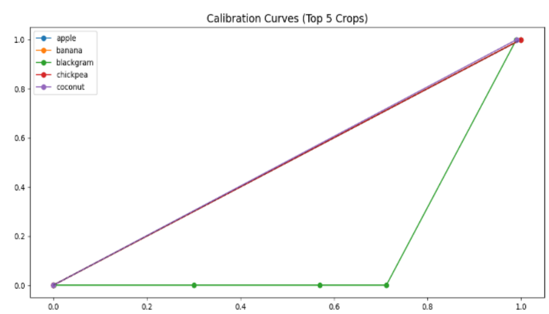

Fig 5: Calibration curves for the top five crop classes predicted by the proposed MB-EFF model

The calibration curves of the proposed MB-EFF model for the top five most common crop classes (apple, banana, blackgram, chickpea, and coconut) are shown in Fig.5. These are curves between probabilities of predicted and verified outcomes which provide some insights into the predictive reliability of confidence in a model. This implies that most of the crop classes follows the ideal diagonal shown by Figure 5, the predicted probabilities are fairly well calibrated and close to true probabilities. Small deviations for some of the classes indicate class-specific probability uncertainty estimates under a small number of instances, and not systematic bias. Finally the calibration analysis confirms that the developed MB-EFF model not only achieves high prediction accuracy but also provides well calibrated and interpretable probability estimates needed in decision support applications in precision agriculture.

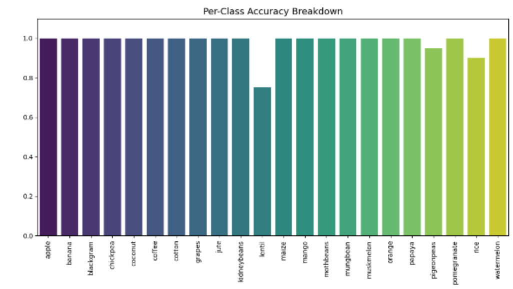

Fig 6: Per-class classification accuracy of the proposed MB-EFF model across crop categories

Your class-wise crop performance details via the proposed Multi-Branch environmental feature fusion(MB-EFF) model are shown in figure 6. Overall accuracy of classification is therefore exceptional, with numerous class classes accurate to near-pure/perfect accuracy that suggests very focused capacity of distinguishing specific vector group in class soil and environment. Still, for a few classes viz., lentil and rice, we observe a slight decline in accuracy owing to overlapping features distributions or higher interclass similarity. Ultimately, the MB-EFF method offers a reliable and applicable multi-class crop recommendation system with consistent accuracy observed across different types of crops indicating its robustness and stability.

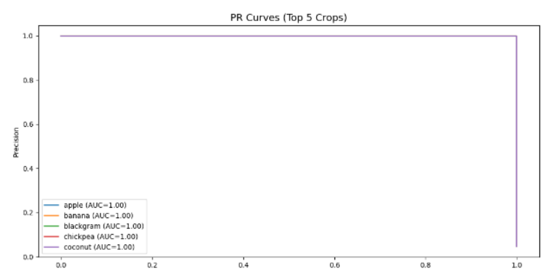

Fig 7: Precision–Recall (PR) curves for the top five crop classes predicted by the proposed MB-EFF model.

Fig. 7 Precision–Recall (PR) curves of the proposed Multi-Branch Environmental Feature Fusion (MB-EFF) model for top 5 crop classes (apple, banana, blackgram, chickpea, and coconut) The curves are near the upper-right section of the PR space, which translates to an 1.00 Area Under the Curve (AUC), that is, perfect precision and recall performance for all considered decision thresholds. This shows that the model is good at distinguishing between positive instances, without over predicting the false positives, which is true even for multi-class settings. The consistently high PR-AUC outcomes validates the proposed architecture by confirming it is capable of resolving class separability and enabling reliable classification outputs for precision agriculture applications.

Table 1: Class-wise precision, recall, F1-score, and support for the proposed MB-EFF crop classification model.

	Precision	Recall	F1-Score	Support
apple	1.00	1.00	1.00	20
banana	1.00	1.00	1.00	20
blackgram	0.91	1.00	0.95	20
chickpea	1.00	1.00	1.00	20
coconut	1.00	1.00	1.00	20
coffee	1.00	1.00	1.00	20
cotton	1.00	1.00	1.00	20

grapes	1.00	1.00	1.00	20
jute	0.91	1.00	0.95	20
kidneybeans	0.95	1.00	0.98	20
lentil	1.00	0.75	0.86	20
maize	1.00	1.00	1.00	20
mango	1.00	1.00	1.00	20
mothbeans	0.87	1.00	0.93	20
mungbean	1.00	1.00	1.00	20
muskmelon	1.00	1.00	1.00	20
orange	1.00	1.00	1.00	20
papaya	1.00	1.00	1.00	20
pigeonpeas	1.00	0.95	0.97	20
pomegranate	1.00	1.00	1.00	20
rice	1.00	0.90	0.95	20
watermelon	1.00	1.00	1.00	20
accuracy			0.98	440
macro avg	0.98	0.98	0.98	440
weighted avg	0.98	0.98	0.98	440

In Table 1, the class-wise performance of proposed Multi-Branch Environmental Feature Fusion (MB-EFF) in terms of precision, recall, F1-score, and support over crop types. The results demonstrate that most crop classes had perfect or near-perfect precision and recall (and thus F1-scores at nearly 1.00), suggesting highly reliable classification. The other classes like lentil, rice and pigeonpeas show some drop in recall which means, there existed some confusion due to specific environmental or soil charateristics between classes. Consistently high generalization capability (98% Accuracy), robust performance (macro-averaged and weighted-averaged F1-scores of 0.98), and balanced performance across all classes facilitates the conclusive verification of the proposed model.

5. Conclusion

This paper introduces a deep learning model called Multi-Branch Environmental Feature Fusion (MB-EFF) for accurate multi-class crop classification from soil nutrient and environmental attributes. It contains an experimental architecture that linearly decomposes chemical and environmental features for each molecule into parallel learning branches, with a competent fusion mechanism that implements squeeze-and-excitation based feature recalibration. This architecture allows the model to learn both domain-related patterns and cross-feature dependencies, while standardized input pre-processing and deep non-linear reasoning layers allow for stable optimization and quick convergence.

Extensive experimental results confirm the efficacy of the proposed method achieving 98% overall classification accuracy with macro-averaged and weighted-averaged precision, recall, and F1-scores of 0.98. All crop classes achieve perfect or close to perfect performance indicating high class separability and generalization performance. Some small performance discrepancies between classes are mostly due to highly overlapping agronomic traits rather than any model failures. To conclude, MB-EFF is an adequate, interpretable, scalable and reliable model for precision agriculture and crop recommendation that shows high real-world applicability and strong prospects for future extensions on larger and more diverse data sets.

REFERENCES

1. Zhao, L., Zhang, J., Yang, H., Xiao, C., & Wei, Y. (2025). A Multi-Branch Deep Learning Network for Crop Classification Based on GF-2 Remote Sensing. *Remote Sensing*, *17*(16), 2852.
2. Wenbo, Z., Ziyang, Z., Chengyu, X., & Qingshan, Z. (2026). Multi Branch Model Based on Cross Scale Feature Fusion for Wheat Seedling Variety Recognition. *Smart Agricultural Technology*, 101785.
3. She, S., Xiao, Z., & Zhou, Y. (2025). Maize Yield Prediction via Multi-Branch Feature Extraction and Cross-Attention Enhanced Multimodal Data Fusion. *Agronomy*, *15*(9), 2199.
4. Li, C., Wang, Y., Fang, Z., & Li, P. (2024). Hyperspectral Image Classification Based on Multi-Branch Adaptive Feature Fusion Network. *IEEE Transactions on Geoscience and Remote Sensing*.
5. Lu, T., Gao, M., & Wang, L. (2023). Crop classification in high-resolution remote sensing images based on multi-scale feature fusion semantic segmentation model. *Frontiers in Plant Science*, *14*, 1196634.
6. Wu, H., Zhou, H., Wang, A., & Iwahori, Y. (2022). Precise crop classification of hyperspectral images using multi-branch feature fusion and dilation-based MLP. *Remote Sensing*, *14*(11), 2713.
7. Kong, J., Wang, H., Wang, X., Jin, X., Fang, X., & Lin, S. (2021). Multi-stream hybrid architecture based on cross-level fusion strategy for fine-grained crop species recognition in precision agriculture. *Computers and Electronics in Agriculture*, *185*, 106134.
8. Islam, M. R., Islam, M. T., Uddin, M. P., & Ulhaq, A. (2024). Improving hyperspectral image classification with compact multi-branch deep learning. *Remote Sensing*, *16*(12), 2069.
9. Dong, W., Wang, X., Ning, S., Zhou, W., Gao, S., Li, C., ... & Sheng, J. (2025). Multi-Scale Multi-Branch Convolutional Neural Network on Google Earth Engine for Root-Zone Soil Salinity Retrieval in Arid Agricultural Areas. *Agronomy*, *15*(11), 2534.
10. Miao, J., Gao, J., Wang, L., Luo, L., & Pu, Z. (2025). Deep Learning Application of Fruit Planting Classification Based on Multi-Source Remote Sensing Images. *Applied Sciences*, *15*(20), 10995.
11. Xie, J., Li, A., Zhang, J., & Cheng, Z. (2019). An integrated wildlife recognition model based on multi-branch aggregation and squeeze-and-excitation network. *Applied Sciences*, *9*(14), 2794.
12. Hu, J., Shen, L., & Sun, G. (2018). Squeeze-and-excitation networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 7132-7141).
13. Gong, Y., Wu, H., Zhou, J., Zhang, Y., & Zhang, L. (2025). Hybrid Multi-Branch Attention–CNN–BiLSTM Forecast Model for Reservoir Capacities of Pumped Storage Hydropower Plant. *Energies*, *18*(12), 3057.
14. Anandamurugan, S. (2025). Hybrid deep learning with a fusion model of weather and soil-based multi-crop recommendations for improving crop sustainability. *Theoretical and Applied Climatology*, *156*(11), 1-25.
15. Wang, G., Gao, Y., Xu, F., Sang, W., Han, Y., & Liu, Q. (2025). A Banana Ripeness Detection Model Based on Improved YOLOv9c Multifactor Complex Scenarios. *Symmetry*, *17*(2), 231.
16. Celik, G. (2025). Multi-layer feature fusion for high-accuracy solid waste classification using a hybrid deep learning model. *The Visual Computer*, 1-23.
17. Tang, Z., Pan, X., She, X., Ma, J., & Zhao, J. (2025). Detail and Deep Feature Multi-Branch Fusion Network for High-Resolution Farmland Remote-Sensing Segmentation. *Remote Sensing*, *17*(5), 789.
18. Lin, Z., Liu, W., Wang, S., Pan, J., Fu, R., Chen, T., & Lin, T. (2025). Strawberry harvest date prediction using multi-feature fusion deep learning in plant factory. *Computers and Electronics in Agriculture*, *234*, 110174.
19. Wang, C., Ni, P., & Cao, M. (2021, July). Research on crop disease recognition based on Multi-Branch ResNet-18. In *Journal of Physics: Conference Series* (Vol. 1961, No. 1, p. 012009). IOP Publishing.
20. Li, P., Gong, X., Hu, X., Shi, L., Xue, X., Guo, J., ... & Gan, D. (2019, April). Plant identification based on multi-branch convolutional neural network with attention. In *Chinese Conference on Image and Graphics Technologies* (pp. 472-481). Singapore: Springer Singapore.