

An Explainable Uncertainty-Weighted Multi-Task Learning Framework for Joint Crop Recommendation and NPK Prediction with Probabilistic Crop Conditioning

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Abstract: Crop selection and fertilizer planning are of generally based on farmer experience, even though suitable crops and nutrient needs depend on soil and environmental conditions that vary between fields. In many existing systems, crop recommendation and nutrient prediction are handled by separate models, and few explain how reliable a given prediction is. This study proposes a multi-task learning model that predicts the recommended crop and the nitrogen, phosphorus, and potassium (NPK) requirement from seven pre crop inputs: soil type, season, soil pH, temperature, water requirement, relative humidity, and water source. A shared network feeds a crop classification head and an NPK regression head. The NPK head receives the full predicted crop probability vector instead of the true crop label, and the two task losses are balanced using learned uncertainty parameters. Monte Carlo Dropout estimates the uncertainty of each prediction, and SHAP shows which inputs drove it. On a dataset of 57,000 observations covering 57 crops, the model reached an accuracy of 0.9496 and a macro F1-score of 0.9463 for crop classification, below Random Forest (0.9627) and XGBoost (0.9618). The mean NPK R^2 was 0.8537, compared with 0.8518 for XGBoost and 0.8501 for a standalone DNN. The calibration error was 0.0072, and results were stable across five random seeds. SHAP showed that soil type, season, and relative humidity contributed most to both tasks. The trained model was built into a recommendation system that returns a crop, NPK values with uncertainty intervals, and an explanation.

Keywords: Crop recommendation, multi-task learning, NPK prediction, uncertainty estimation, SHAP

I. INTRODUCTION

Agriculture is an important sector of human society, from making it possible for humans to settle in one place instead of living as nomads to being the basis of modern day food production. One of the main tasks in farming is to choose a suitable crop to grow in the available soil and environmental factor. Farmers primarily select crops based on their experience, traditional knowledge, local culture or previous cultivation. Such knowledge is valuable, but these methods may not always be a good way to decide which crops to grow as soil conditions may differ, environmental factors may be different from one field to another as well as from one year to the next. Farmers also need to decide the appropriate amount of nutrient required for the recommended crop to grow in a specific environment condition. Choosing an unsuitable crop or applying unsuitable nutrient treatment can affect the crop growth, yield, and the quality of soil. So, choosing a suitable crop and the suitable nutrient for that crop in that particular area is a very important task.



Because the selection of a suitable crop and nutrient treatment is important, several studies have focused on improving crop selection and nutrient management based on soil and environmental factors. Previous studies have used machine learning models such as Random Forest, XGBoost, SVM, and K-Nearest Neighbors for crop recommendation using soil and climatic recommendations information. These studies commonly use features such as N, P, K, soil pH, temperature, humidity, and rainfall and have reported good classification performance on their respective datasets [1] [2]. Some studies have also used explainability methods such as LIME and SHAP to show why a particular crop was recommended [3] [4]. For NPK prediction, previous studies have used MLR (multiple linear regression) for predicting the NPK [5] some studies have used Enhanced Genetic Algorithm for the same task [6] using the various soil and environmental factors like soil pH, temperature, humidity, rainfall as input features. A study does uncertainty estimation using NGBost's parametric Gaussian output on a single regression task (total NPK amount, not separated N/P/K) [7]. Other studies have considered crop classification together with fertilizer or nutrient prediction. However, these tasks have generally been handled using separate models, even when they use the same dataset, rather than learning both tasks together in a single model [8]. Multi-task learning can also be used as it provides shared representation. . Studies also show that task uncertainty can be learned during training to balance different losses instead of manually assigning fixed weights to each task. [9]

Existing crop recommendation studies that use explainability mainly focus on crop classification and do not have a NPK prediction along with the crop recommendation. Studies that predict recommendations both crop and NPK values generally use a separate model for each task, the two tasks are not learned together through a shared representation. The use of uncertainty estimation together with crop recommendation is limited, specifically when both during training(task-level uncertainty) and during inference (predictive uncertainty) are considered.

Based on this observation, this study proposes a multi-task learning framework for predicting crop recommendations and NPK (nitrogen, phosphorus, and potassium) within a single framework using pre-crop soil, seasonal, and environmental information. The framework uses a shared neural representation for both tasks with separate task-specific heads. The NPK prediction branch does not receive the actual crop label. Instead, it receives the full predicted probability distribution over the crop classes along with the shared representation, allowing the predicted crop information to contribute to NPK prediction without directly using the true crop label. The classification and regression losses are balanced using learned homoscedastic uncertainty parameters. It also uses Monte Carlo Dropout[22] during inference to estimate predictive uncertainty and SHAP [10] for explaining the factors contributing to the crop recommendations. Its performance is evaluated against Random Forest, XGBoost, and a standalone deep neural network, along with assessments of calibration and stability across random seeds.

II. METHODOLOGY

A. Data Preprocessing

1) Feature Eligibility and Leakage Control :

Each candidate feature was checked for its correlation with the prediction target to identify the variables that could leak target information into the input set. The correlation was measured using the Pearson correlation coefficient:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{[\sum (x_i - \bar{x})^2 \cdot \sum (y_i - \bar{y})^2]}}$$

2) Encoding and Standardization :

Categorical variables were transformed into the numerical representation using one hot encoding. Numerical variables were standardized using z-score standardization:

$$x' = (x - \mu) / \sigma$$

where μ and σ are computed only from the training set.

3) Train-Validation-Test Split :

The dataset was divided into train-validation-test subsets using stratified sampling.



B. Baseline Models

1) **Random Forest** : It is an ensemble method that trains multiple decision trees on bootstrapped subsets of the training data and combines their output through majority voting (classification), reducing the variance of a single decision tree.

2) **XGBoost** : It is a gradient boosting method that builds an ensemble of decision tree sequentially, where each new tree is trained to reduce the residual error of the combined ensemble so far, using the gradient descent on a differentiable loss function with regularization to control overfitting.

3) **DNN** : A standard feedforward neural network was trained separately for classification and for regression, as a single task baseline. This isolates the effect of joint multi task learning from the effect of simple using a neural network architecture.

C. Proposed Multi-Task Learning Model

1) **Multi Task Learning architecture and formulation** : In hard-parameter-sharing-multi-task learning, a shared representation is learned from the input and used by multiple task specific output heads :

$$h = f_{shared}(x)$$

$$\hat{y}_{class} = g_{class}(h)$$

$$\hat{y}_{reg} = g_{reg}(h)$$

Where f_{shared} is a shared feature extractor and g_{class} , g_{reg} are separate output heads for classification and regression respectively, trained jointly so that the representation captures information useful to both tasks.

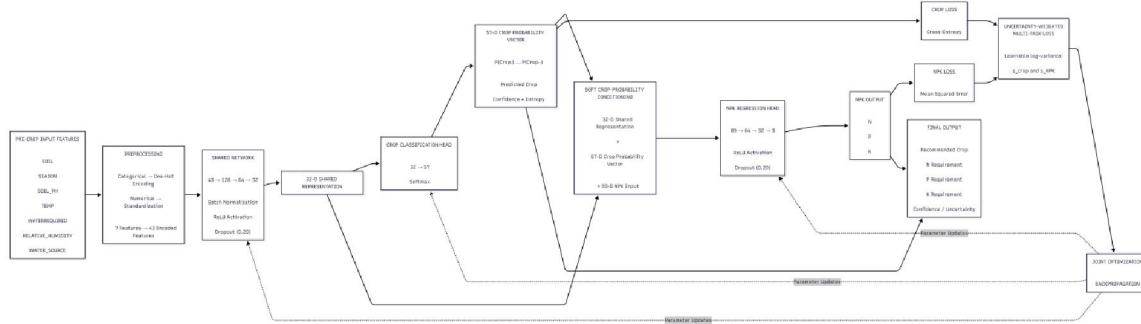


Figure 1. Architecture of proposed MTL model (Monte Carlo Dropout, described in Section II-C-5, is applied to this same trained architecture at deployed model.)

2) **Uncertainty-Weighted Multi-Task Loss** : The contribution of each task to the overall training objective is determined during training rather than explicitly specified in advance. This is achieved by introduction task-specific uncertainty parameter, following the uncertainty based weighted strategy of Kendall and Cipolla.

$$L = e^{(-s_1)} L_1 + s_1 + e^{(-s_2)} L_2 + s_2$$

where L_1 , L_2 are the individual task losses and s_1 , s_2 are learned log-variance parameters, updated jointly with the network weights during training.

3) **Calibration and Predictive Uncertainty** : For classification the confidence is the largest predictive crop probability

$$conf = \max_k p_k$$

Predictive entropy measures how widely the probability is spread across K classes

$$H = -\sum_{k=1}^K p_k \cdot \log(p_k + \epsilon)$$

Where ϵ is a small constant for numerical stability. Confidence is highest and entropy is lowest when the probability is concentrated on one class.

Model calibration measures whether predicted confidence matches observed accuracy and is quantified using Expected Calibration Error (ECE) :

$$ECE = \sum_{i=1}^M (|B|/n) \cdot |acc(B) - conf(B)|$$



Where predictions are grouped into M confidence bins, and $\text{acc}(B_{\square})$, $\text{conf}(B_{\square})$ are the average accuracy and average predicted confidence within bin $B_{\square}$.

4) SHAP Based Explanation : SHAP assigns each input feature a contribution value based on Shapley values from cooperative game theory, representing a feature's average marginal contribution to the prediction across all possible subsets of the other features:

$$\phi_i = \sum_{S \subseteq F \setminus i} [|S|! (|F| - |S| - 1)! / |F|!] \cdot [f(S \cup i) - f(S)]$$

where F is the full feature set, S is a subset excluding feature i , and $f(S)$ is the model's prediction using only the features in S .

5) Monte Carlo Dropout : Predictive uncertainty can be estimated without retraining the model. Dropout can be kept active during prediction and same input is passed through the model T times. The mean of these predictions is the final prediction, while their standard deviation indicates the uncertainty.

$$\hat{y}_{mean} = (1/T) \sum_{t=1}^T \hat{y}_t$$

$$\hat{y}_{std} = \sqrt{[(1/(T-1)) \sum_{t=1}^T (\hat{y}_t - \hat{y}_{mean})^2]}$$

III. DATASET DESCRIPTION

The dataset was obtained from Mendeley Data Repository ("Crop Recommendation Dataset", CC by 4.0)[21] and contains 57,000 observations across 57 crop classes (1,000 observation per crop), with 23 original variables having crop identity, soil properties, seasonal and water related variables, environmental condition, and nutrient requirement. No missing values and duplicate values were found.

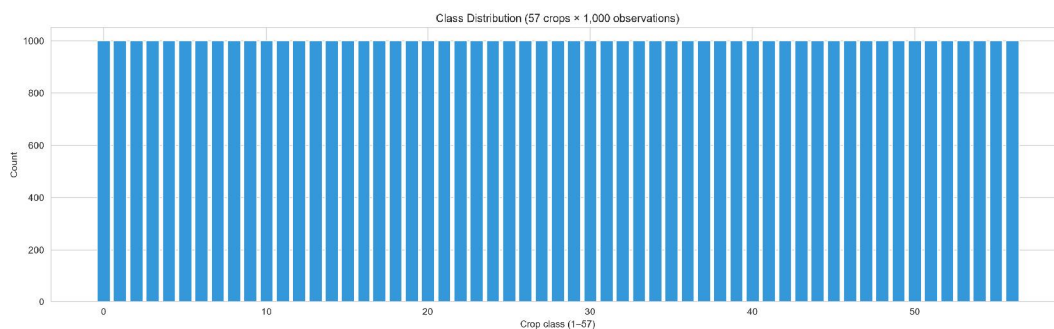


Figure 2. Class distribution of crop recommendation dataset

IV. EXPERIMENTAL WORK

A. Data Preprocessing

1) Feature eligibility and leakage control : Correlation analysis identified strong correlation between the NPK targets and their maximum values counterpart as shown in fig.3 ($r = 0.944$, 0.884 and 0.956 for N, P, K respectively). N_MAX , P_MAX , K_MAX with $TYPE_OF_CROP$, $SOWN$, $HARVESTED$ and $CROP_DURATION$, were excluded as each of them either directly identifies the crop or is only known after crop has already been selected. The final input set retained seven pre crop variables : soil, soil pH, water requirement, season, temperature, relative humidity and water source.



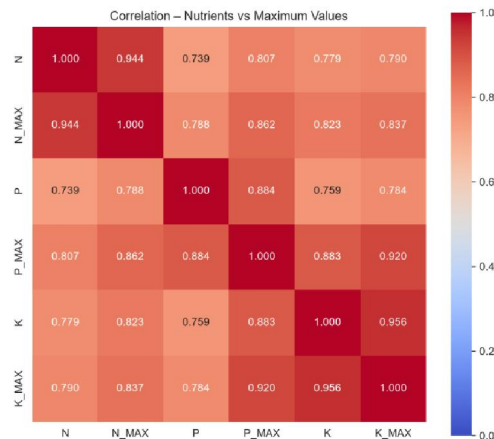


Figure 3. Correlation matrix of NPK and their Maximum value variable

2) **Encoding and Standardization** : Categorical variables were one hot encoded and numerical variables were standardized, giving 43 input features.

3) **Train – Validation – Test Split** : The dataset was split 70:15:15 (train : validation : test) with stratification by crop class (39,900/8,550/8,550 sample), and used a fixed random seed of 42.

B. Baseline Models

The results of the Baseline model that are trained separately for crop classification (Random Forest, XGBoost, DNN) and NPK recommendation (XGBoost, DNN) are as follow:

Table I. Results of Baseline model (Crop Classification)

Model	Accuracy	Macro Precision	Macro Recall	Macro F1
Random Forest	0.9629	0.9627	0.9627	0.9627
XGBoost	0.9623	0.9631	0.9623	0.9618
DNN	0.9494	0.9549	0.9494	0.9485

Table II. Results of Baseline Model (NPK recommendation)

Model	Mean R ²	Mean MAE	Mean RMSE
XGBoost	0.8518	7.6045	9.5771
DNN	0.8501	7.6432	9.6762

C. Proposed Multi Task Learning Model

1) **Model Architecture** : The model was implemented in PyTorch (2.10.0+cpu) and trained on CPU using the Adam optimizer (learning rate 0.001, weight decay 1×10^{-4} , batch size 128) for a maximum of 150 epochs, with early stopping (patience 15) on validation loss. To check whether the results depend on a particular initialization, the model was also trained with five random seeds (42, 7, 21, 77, 123), with all other settings held fixed.

The MTL model uses a shared backbone of three connected hidden layers (128, 64, 32 units) with ReLU activation, batch normalization, and 0.20 dropout after the first two layers. There are two heads from the shared 32 representations. The crop classification head produces 57 class scores, which are converted into probabilities using the softmax function:

$$\hat{y}_{crop} = \text{softmax}(W_c \cdot h + b_c)$$

The NPK regression head receives the shared representation (32) and the 57 crop probability distribution.

$$\hat{y}_{NPK} = f_{NPK}([h; \hat{y}_{crop}])$$



where $h \in \mathbb{R}^{32}$ is the shared representation, $\hat{y}_{crop} \in \mathbb{R}^{57}$ is the predicted crop-probability vector, and f_{NPK} is the $89 \rightarrow 64 \rightarrow 32 \rightarrow 3$ regression head (0.20 dropout after its first layer). The true crop label is not passed to NPK head at any point of computation.

The remaining components of the proposed model are evaluated at different scopes. Calibration and the global SHAP analysis are done across full test set. Local SHAP explanation is done on case study based (3 cases, 2 correct, 1 incorrect). Monte Carlo Dropout uncertainty is demonstrated on a real time input in the deployed system.

2) Uncertainty Weighted Loss : Training and Validation loss curve shows that both parameters decreased from their initial value of zero and stabilized after approximately 40 epochs.

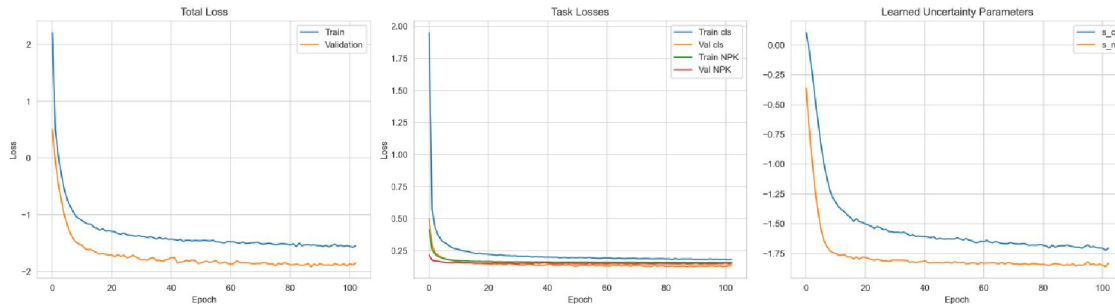


Figure 4. Training and Validation loss curves

3) Calibration : Model Calibration was evaluation using Expected Calibration Error (ECE). It measures the average difference between predicted confidence and observed accuracy across confidence bins. The proposed model achieved the ECE of 0.0072 on the test set. Fig.5 shows the reliability diagram.

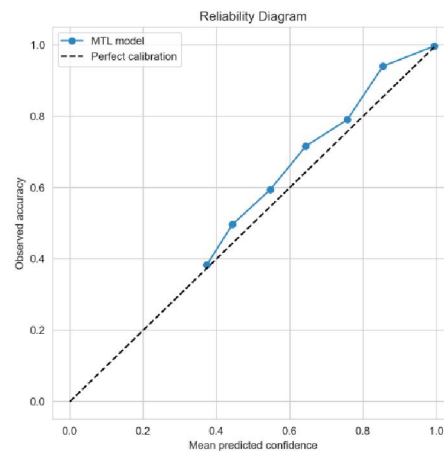


Figure 5. Model Calibration – ECE

Fig.6 shows correct predictions were concentrated near a confidence of 1.0 and an entropy near 0 (mean confidence 0.9628, mean entropy 0.0943). Incorrect prediction had lower confidence mostly between 0.35 to 0.65 and higher entropy (mean confidence 0.5572, mean entropy 0.9559).



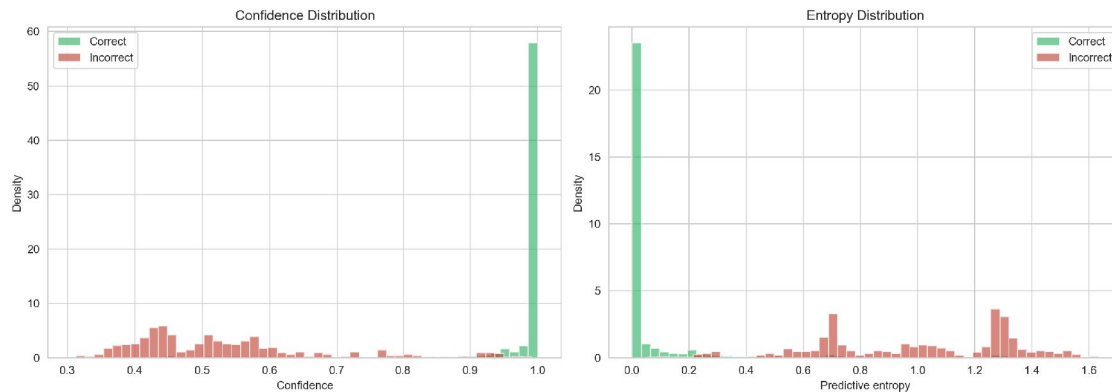


Figure 6. Distribution of Confidence and Predictive Entropy

4) SHAP based explanations (Global and Local) : Global feature importance was computed on test set using SHAP's PermutationExplainer. Fig.7 shows the mean absolute SHAP values for each of the seven input features, expressed as percentage of total contribution, separately for crop classification and NPK prediction.

Local SHAP was computed on three case study based inference along with confidence and entropy, where two of them are correct crop classification and one is incorrect. Fig.8 shows the local SHAP explanations on case study.

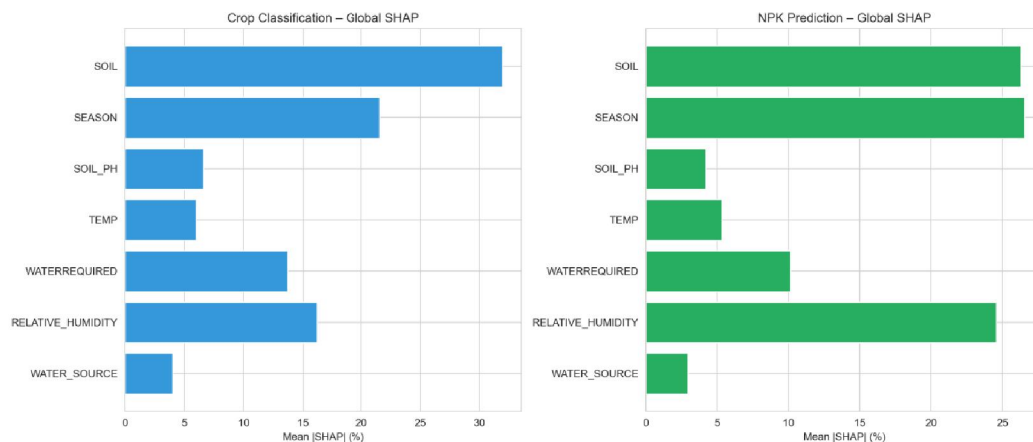


Figure 7. SHAP explanations on full test set

Local SHAP Explanations – Representative Cases

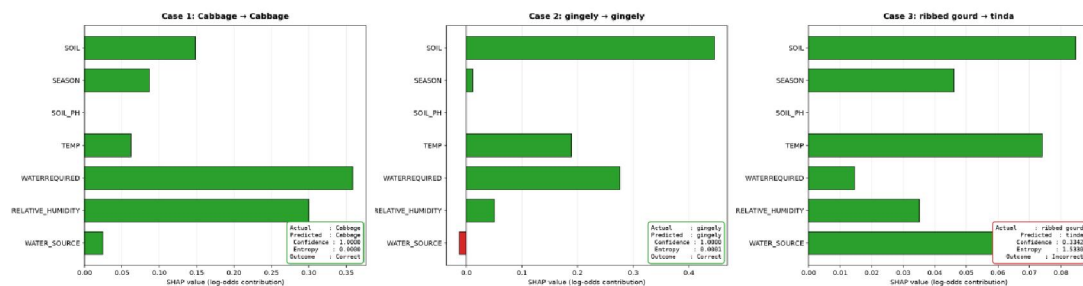


Figure 8. Local SHAP explanations for case study based inference



V. DEPLOYED MODEL

Using the methods described in section II Methodology, a working recommendation system was built around the trained multi task learning model. The system takes seven input from user: soil type, season, soil pH, temperature, water required, relative humidity and water source. The inputs follow same preprocessing procedures described in section II-A-1 & 2, then passed through the trained architecture (fig.1 section IV-C-1). The crop with the highest predicted probability is returned as the recommended crop. The NPK head uses the full crop probability vector, as in training, to predict the N, P, and K values.

Monte Carlo Dropout (Section-II-C) was used in deployed model for uncertainty estimation. The dropout layers are reactivated at inference, batch normalization is kept in evaluation mode and 100 stochastic forward passes are run on the same input. For NPK prediction, the mean and standard deviation are calculated, along with an approximate 95% interval using mean $\pm$ 1.96 standard deviation. The average crop probability across all present is also calculated, together with the deterministic confidence and entropy of the crop prediction.

A local SHAP explanation for the system is produced with GradientExplainer, instead of PermutationExplainer for faster single input inference.

Fig.9 shows the system output for example input: Alluvial Soil, Kharif season, pH 7.0, Temperature 32.0 C, Water Available 1800.0, Relative Humidity 68.0%, Water source Irrigated. The system recommended rice with a deterministic confidence of 100% and an entropy of 0.0000. The predicted N, P, and K values were 89.47, 50.03, and 50.25. Across the 100 Monte Carlo passes, the mean predictions were 89.09 ± 2.27 for N, 49.95 ± 0.68 for P, and 50.50 ± 0.85 for K, giving approximate 95% of intervals. The local SHAP explanation ranked the contribution of inputs as water available 36.30%, soil 21.79%, season 21.23% and smaller contribution from relative humidity, temperature, soil pH, and water source.

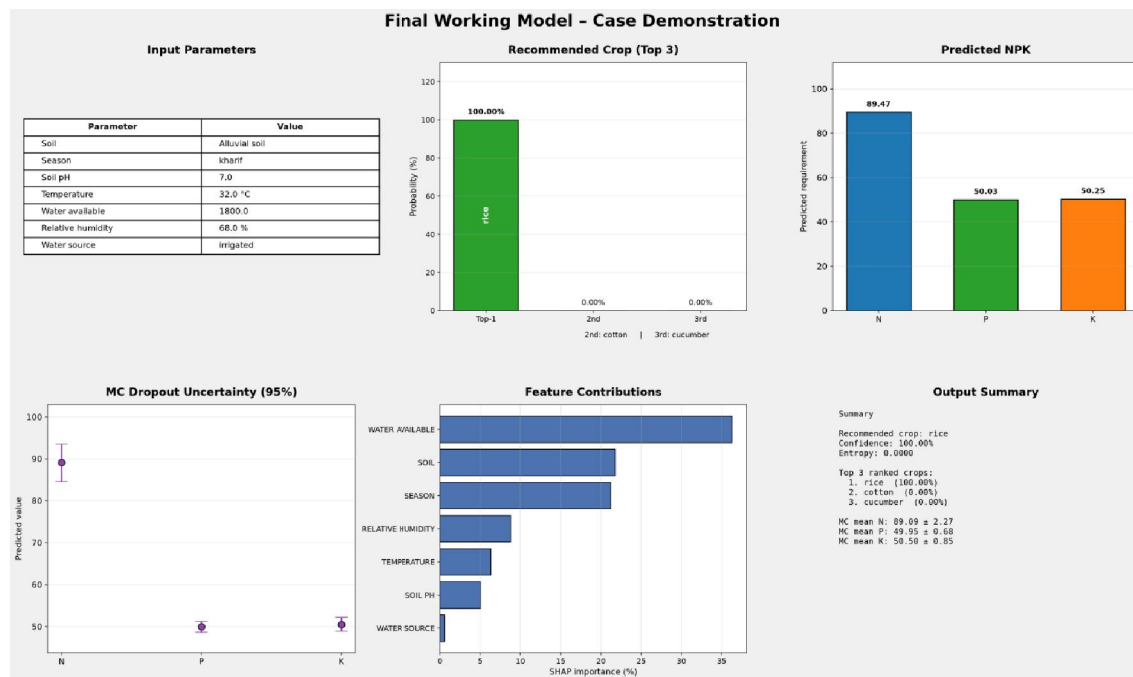


Figure 9. Case Demonstration of Deployed Model

VI. RESULT ANALYSIS

1) Comparative Analysis : On the test set of 8,550 samples across 57 crops, the proposed model reached an accuracy of 0.9496 and a macro F1-score of 0.9463 for crop classification, and a mean NPK R^2 of 0.8537 with a mean MAE of



7.5763 for NPK prediction. Across five random seeds (42, 7, 21, 77, 123), crop accuracy was 0.9497 ± 0.0020 and mean NPK R^2 was 0.8540 ± 0.0011 , so the results are not specific to one initialization. Tables 3 and 4 compare the model with the baselines.

Table III. Results of MTL against Baseline model (Crop Classification)

Model	Accuracy	Macro F1
Random Forest	0.9629	0.9627
XGBoost	0.9623	0.9618
DNN	0.9494	0.9485
MTL model	0.9496	0.9463

For crop classification (Table 3), Random Forest and XGBoost reached higher accuracy than the proposed model (0.9629 and 0.9623, against 0.9496). The proposed model's accuracy was close to that of the DNN (0.9494), while its macro F1-score (0.9463) was 0.0022 lower than the DNN's (0.9485). One possible reason for the gap with the tree-based models is that they handle the one-hot categorical inputs of tabular data well. Another is that the shared network of the proposed model also has to support the NPK task. Neither explanation was tested.

Table IV. Results of MTL against Baseline Model (NPK recommendation)

Model	Mean R^2	Mean MAE
XGBoost	0.8518	7.6045
DNN	0.8501	7.6432
MTL model	0.8537	7.5763

For NPK prediction (Table 4), the proposed model had the highest mean R^2 (0.8537) and the lowest mean MAE (7.5763), compared with 0.8518 and 7.6045 for XGBoost and 0.8501 and 7.6432 for the DNN. The R^2 difference from XGBoost (0.0019) is small, and the model's own R^2 varied by ± 0.0011 across seeds. No significance test was run, so the NPK result is better read as comparable to the baselines than as an improvement.

The baselines are separate single-task models, while the proposed model produces both outputs from one shared network and does not give the NPK head the true crop label. Calibration, uncertainty, and SHAP analysis were evaluated for the proposed model only, so Tables 3 and 4 compare predictive accuracy alone.

2) Error Analysis:

Fig.10 shows the per crop macro F1 score for all 57 crops, ranked from lowest of highest. Most crop scored above macro average and many reached F1 score close to 1.0. Lowest performance classes were Ribbed Gourd (about 0.33), Muskmelon (about 0.52), Annual Moringa (about 0.57), and Tinda (about 0.60). Castor followed at about 0.89, while Brinjal reached about 0.96, and every other crop scored above 0.90.

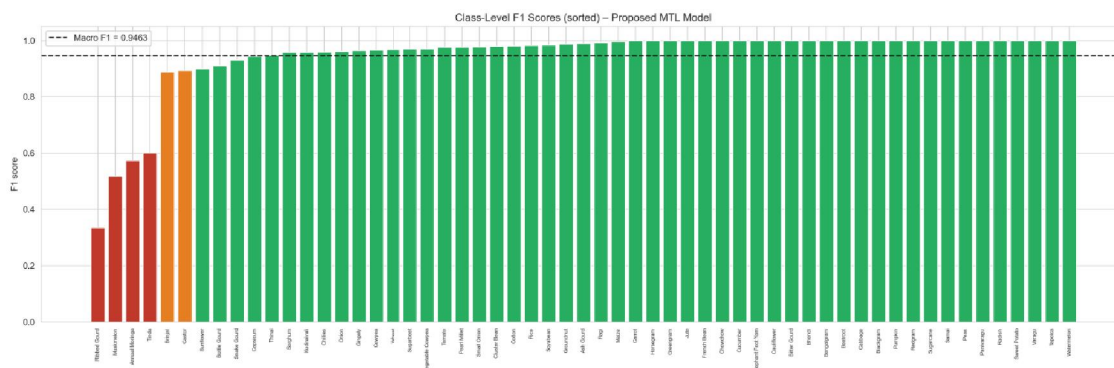


Figure 10. Macro F1 score of all 57 crop classes

Fig.11 shows the confusion matrix of most frequently confused crops. Errors were concentrated among four crops: Ribbed Gourd, Muskmelon, Annual Moringa, and Tinda. Ribbed Gourd was the weakest crop only 23% samples were classified as correct and the rest spread across Muskmelon (26%), Annual Moringa (25%) and Tinda (24%)



remaining 2% spread across other classes. Muskmelon was classified as Tinda in 42% of cases and Tinda as Muskmelon in 17%. Annual moringa was correctly classified in 51% of cases. The four weakest crop confused with each another, which may be interpreted that their seven input features overlap heavily (this is an interpretation and was not tested directly).

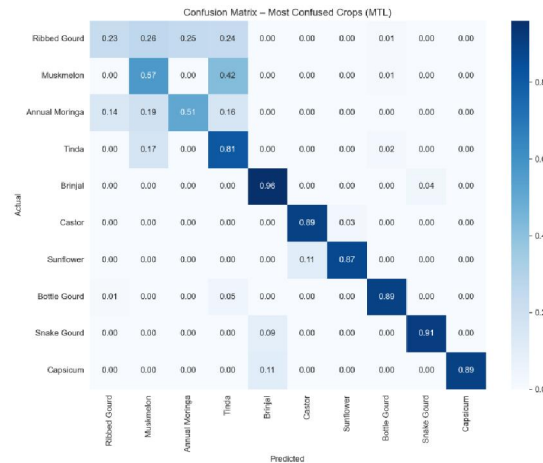


Figure 11. Confusion Matrix of most confused crops

VII. DISCUSSION

The proposed multi-task learning framework jointly recommends crops and predicts NPK requirements. Its key finding is that the NPK head, using the predicted crop-probability distribution instead of true labels, achieved a mean R^2 of 0.8537, outperforming XGBoost and standalone DNN baselines. This supports the hypothesis that shared representations and probabilistic crop conditioning enable effective information sharing between tasks. For crop classification, accuracy was 0.9496, slightly below tree-based baselines, likely because ensemble methods handle one-hot tabular data well and the shared network must balance both tasks. Results were stable across five seeds (*crop accuracy varied by ± 0.0020 and NPK R^2 by ± 0.0011 across five seeds*). Calibration was strong (ECE = 0.0072), and confidence/entropy patterns separated correct from incorrect predictions, supporting deployment reliability. Errors concentrated in four crops Ribbed Gourd, Muskmelon, Annual Moringa, and Tinda which were mainly confused with each other, suggesting overlapping input features. SHAP identified soil type, season, and relative humidity as the most influential features for both tasks, aligning with domain knowledge. Lastly, the framework effectively integrates crop recommendation and NPK prediction with useful uncertainty estimates and explanations, though classification performance remains slightly below the strongest baselines.

VIII. CONCLUSION

This paper presented a multi-task learning model that recommends a crop and predicts the N, P, and K requirement from seven pre-crop inputs. The NPK head uses the predicted crop-probability distribution instead of the true crop label, the two losses are balanced by learned uncertainty parameters, and Monte Carlo Dropout and SHAP give an uncertainty estimate and an explanation for each recommendation. For crop classification, the model reached an accuracy of 0.9496 and a macro F1-score of 0.9463, lower than Random Forest (0.9629) and XGBoost (0.9623). For NPK prediction, the mean R^2 was 0.8537 compared with 0.8518 for XGBoost, a small difference given the ± 0.0011 variation across five random seeds. Most classification errors came from four crops (Ribbed Gourd, Muskmelon, Annual Moringa, and Tinda), which were mainly confused with each other. The calibration error was 0.0072, and incorrect predictions had lower confidence and higher entropy than correct ones. SHAP showed that soil type, season, and relative humidity contributed most to both tasks.



The studies reviewed here explained crop classification only, trained separate models for crop and nutrient prediction, or reported uncertainty for NPK alone. The proposed model covers both tasks in one network with uncertainty estimates and explanations.

The study has limits. It uses one dataset of 57 crops and seven pre-crop inputs. The NPK targets are nutrient requirement values from the dataset, not field measurements.

Future work could test the model on independent regional datasets, add inputs such as rainfall and irrigation type, and compare the shared-backbone design with Cross-Stitch Networks [11] or TabNet-based multi-task learning.

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