# Objective: Enhance the accuracy of the initial LSTM model for better time series prediction.

## Changes Made:

* Added an extra LSTM layer to capture deeper temporal patterns.
* Implemented Leaky ReLU activation functions to introduce non-linearity.
* Adjusted dropout rates to 0.2 after each LSTM layer to prevent overfitting.
* Conducted hyperparameter tuning using Keras Tuner:
  + Explored 20 trials with 3 executions per trial.
  + Identified optimal hyperparameters:
    - Number of layers: 3
    - Units per layer: [50, 50, 150]
    - Dropout rates: [0.3, 0.3, 0.4]
    - Learning rate: 0.004591848176101869

## Implementation:

* Updated model configuration with optimal hyperparameters.
* Trained the model over 300 epochs with a batch size of 32, incorporating early stopping.

## Outcome:

* Improved model accuracy in time series prediction tasks based on initial evaluations.
* Pending validation on test datasets to confirm effectiveness.

## Next Steps:

* Evaluate model performance on test datasets for validation.
* Document findings and finalize project analysis.
* Consider further refinements or alternative architectures based on test results.

# **Objective:** Enhance the accuracy of the Gradient Boosting Regressor model for crop price prediction.

## Changes Made:

* **Increased Number of Estimators:**
  + Adjusted from 100 (code 1) to 5000 (code 2) to introduce more ensemble learning iterations, potentially capturing more complex patterns in the data.
* **Adjusted Learning Rate:**
  + Decreased from 0.1 (code 1) to 0.001 (code 2) to slow down the learning process, allowing finer adjustments to model predictions and potentially preventing overfitting.
* **Increased Maximum Depth:**
  + Raised from 3 (code 1) to 8 (code 2) to allow the individual trees within the ensemble to grow deeper, potentially capturing more intricate relationships between features and target variable.
* **Random State Adjustment:**
  + Changed from 42 (code 1) to 84 (code 2) to ensure reproducibility and consistency in model training and evaluation.

## Outcome:

* Improved accuracy observed in crop price prediction tasks based on initial evaluations and metrics analysis.

## Next Steps:

* Perform rigorous evaluation and validation on test datasets to confirm sustained accuracy improvements.
* Document and report findings, including comparison with previous model iterations.
* Consider further optimizations or alternative algorithms based on ongoing performance assessments.

## Visualization

1. **Onion**

**A graph with lines and numbers

Description automatically generated**

1. **Corn**

**A graph with numbers and lines

Description automatically generated**

1. **Potato**

**A graph with different colored lines

Description automatically generated**

## Results

The NN model consistently outperformed the ML model in accuracy for all three crops:

* **Onion:** NN closely follows real-time data; ML shows slight deviations.
* **Corn:** Both models perform well; NN has a marginally better fit.
* **Potato:** NN shows superior accuracy; ML has larger deviations.

## Conclusion

The NN model demonstrates higher accuracy in crop price prediction compared to the ML model, indicating its potential for improving decision-making in agriculture.

## Future Work

Future research should aim to:

* Enhance ML model accuracy through additional tuning and feature engineering.
* Explore additional influencing factors such as weather data, market trends, and geopolitical events.
* Expand the analysis to encompass a broader range of crops and regions for a comprehensive assessment of model performance and applicability.