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: 0.0045918481761 01869

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:

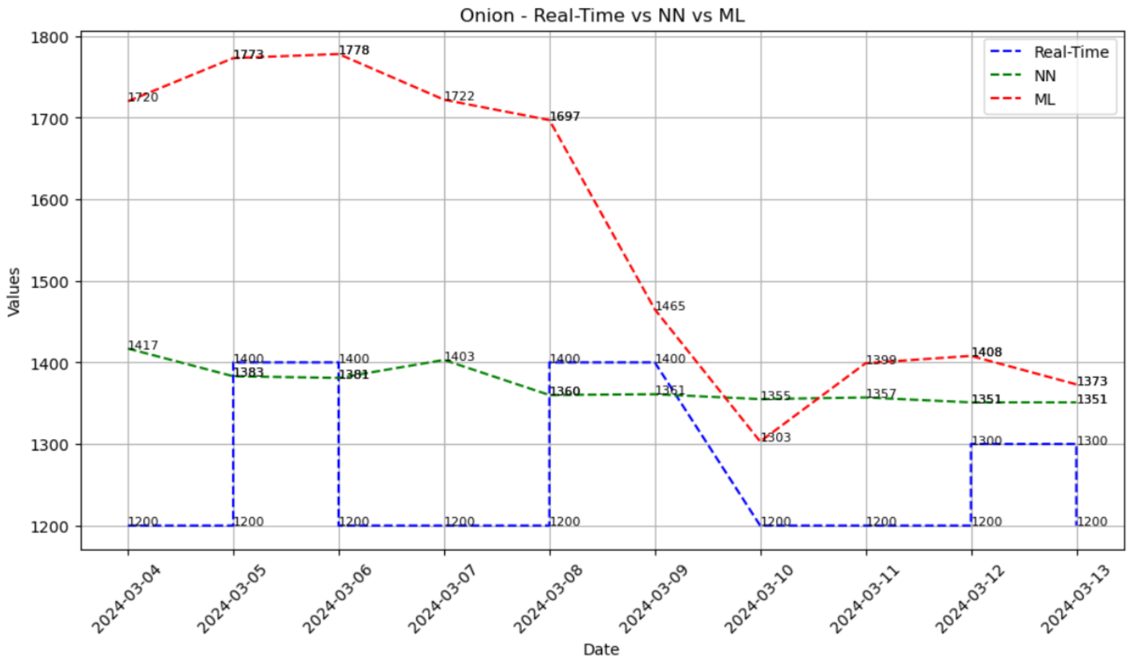
- Improved accuracy observed in crop price prediction tasks based on initial evaluations and metrics analysis.

Next Steps:

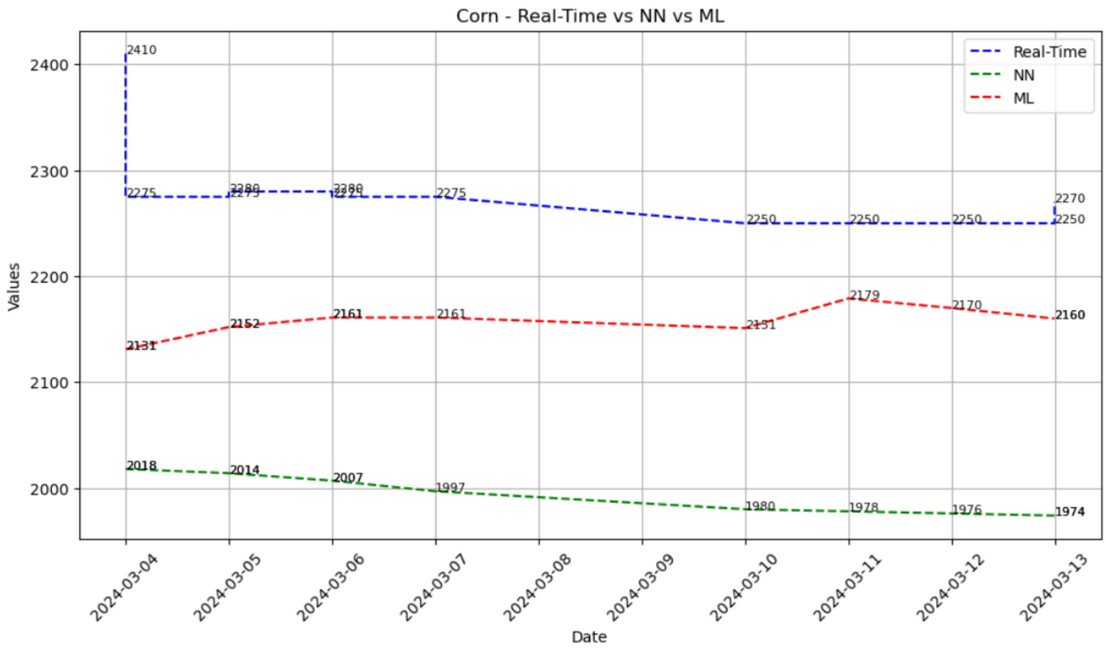
- Perform rigorous evaluation and validation on test datasets to confirm sustained accuracy improvements.
- Document and report findings, including comparison with previous model iterations.
- Consider further optimizations or alternative algorithms based on ongoing performance assessments.

Visualization

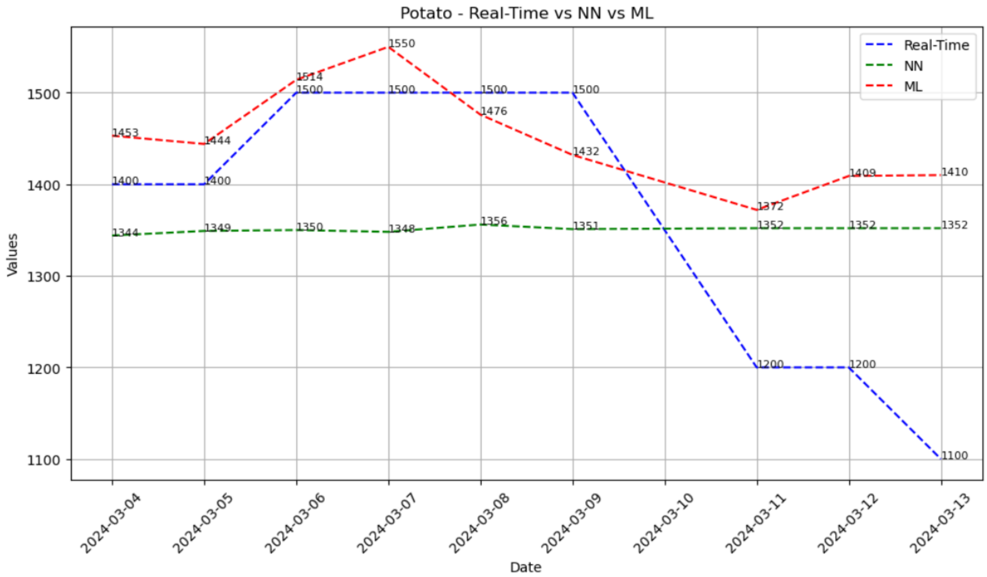
A. Onion



B. Corn



C. Potato



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.