Problem Statement:

NV Games aims to analyze gameplay data from StarCraft II to predict player skill levels based on their actions and behaviors. This will give them insight when creating their own in-game AI. Skill level in games like StarCraft II is highly nuanced, combining factors like multitasking, strategic decision-making, and mechanical speed. Accurately predicting these levels can offer insights into game balance, player progression, and potential matchmaking improvements. Using machine learning, the goal is to identify patterns in player stats (e.g., APM, map exploration, and unit production) that correlate with skill, represented by the LeagueIndex.

Approach:

Data Wrangling:

The dataset initially contained 3,394 rows and 14 columns. Steps included:

- Removing null values and irrelevant columns.
- Normalizing numerical columns for machine learning models.
- Re-mapping the LeagueIndex column to a zero-based range for compatibility with deep learning frameworks.
- Ensuring all features (e.g., APM, Minimap interactions) were clean, scaled, and ready for modeling.

Exploratory Data Analysis (EDA):

- A correlation heatmap revealed weak-to-moderate relationships between individual gameplay stats and LeagueIndex, with no single feature strongly dominating.
- Players in higher leagues demonstrated greater multitasking efficiency and map exploration.
- Outliers in features like APM and MaxTimeStamp were retained, as they reflect legitimate gameplay behavior variations.

Preprocessing and Training Data:

- The dataset was split into training (80%) and testing (20%) sets, ensuring stratification by LeagueIndex.
- The entire numeric dataset was scaled prior to modeling.
- Categorical encoding was unnecessary since all features were numerical.

Modeling:

Three traditional machine learning models and a deep learning model were evaluated:

1. **Random Forest**:
    - Strength: Handles non-linear relationships and feature importance.
    - Performance: Test accuracy of 38%, showing limited ability to capture subtle gameplay patterns.
2. **Gradient Boosting**:
    - Strength: Iteratively improves performance by focusing on misclassified instances.
    - Performance: Test accuracy of 42%, outperforming Random Forest slightly.
3. **Support Vector Machine (SVM)**:
    - Strength: Finds optimal decision boundaries for classifying skill levels.
    - Performance: Achieved 40% accuracy, balancing simplicity and interpretability.
4. **Deep Learning**:
    - Strength: Captures complex, non-linear relationships using multi-layered structures.
    - Loss decreased and accuracy improved steadily with more epochs, eventually plateauing at approximately 0.4, indicating the model had learned as much as it could from the data.

Conclusion:

The models demonstrated that skill in StarCraft II is too multifaceted to be predicted accurately with the provided data. The moderate accuracy scores across all models suggest that no single feature, or even combination of features, strongly defines player skill. I also experimented with other metrics, such as F1 Score, but saw little difference.This finding reinforces the depth and balance of the game, where skill emerges from combinations of strategy, mechanics, and decision-making. The deep learning model highlighted these patterns, with decreasing loss and improving accuracy over epochs, though its accuracy eventually plateaued.

Ideas for Further Research:

1. Integrate gameplay replays or heatmaps to include spatial and temporal data for deeper insights.
2. Explore reinforcement learning to simulate how players might adapt to various game states.

Recommendations for NV Games:

1. Improve Player Progression Tracking: Use models like this to evaluate player progression and provide targeted tips for improvement.
2. Enhance Matchmaking Systems: Develop matchmaking algorithms that balance games using a broader range of gameplay metrics, not just LeagueIndex.