**Stage 3 Summary – Predictive Modelling and Churn Analysis**

In Stage 3 of the Telecommunication Churn Analysis project, we focused on designing, training, and evaluating a predictive model aimed at identifying customers who are at high risk of churning. This stage was instrumental in translating cleaned data into actionable predictions that can inform retention strategies. The process involved the following key steps:

**Step 1: Data Preparation**

We loaded the cleaned and fully encoded dataset from Stage 2. To standardize the input features and enhance model training efficiency, numerical variables including tenure, MonthlyCharges, and a newly engineered TotalServiceCost were scaled using the **StandardScaler** technique. This ensured that features with different scales did not disproportionately influence the learning process of the model.

**Step 2: Train-Test Split**

The dataset was split into training and testing sets using an 80:20 ratio. To preserve the original class distribution (churn vs. no churn), **stratified sampling** was applied during the split. This step was critical to ensuring that the model was trained and evaluated on representative data, especially given the class imbalance.

**Step 3: Model Development**

We constructed a **multi-layer Artificial Neural Network (ANN)** using the TensorFlow/Keras framework. The architecture consisted of multiple dense layers with ReLU activations, interspersed with **Dropout layers** to prevent overfitting. Additionally, we incorporated **EarlyStopping** to terminate training when the validation loss plateaued, thus avoiding unnecessary training cycles and potential model degradation.

**Step 4: Addressing Class Imbalance**

Since the dataset exhibited an imbalance between churners and non-churners, we applied **class weighting** during training. This strategy increased the penalty for misclassifying the minority class (churners), compelling the model to better learn their patterns. As a result, this significantly enhanced the model’s **recall** for churn prediction.

**Step 5: Threshold Tuning**

We adjusted the default prediction threshold from **0.5 to 0.4** to favor recall. This adjustment made the model more sensitive to predicting churn cases, ensuring that more at-risk customers were flagged—even if it led to a modest drop in precision. This trade-off is often acceptable in churn scenarios where missing a churner is more costly than a false alarm.

**Step 6: Model Evaluation**

Model performance was evaluated using the **confusion matrix** and key classification metrics. Notably:

* **Recall (Churn): 0.79** – a substantial improvement, highlighting the model's success in capturing churn cases.
* **Accuracy: 0.73** – indicating balanced overall performance.
* **F1-Score (Churn): 0.61** – reflecting the trade-off between precision and recall, but still acceptable in churn-focused models.

**Major Discoveries**

* **High-risk churners** were typically customers with short tenure, high monthly bills, and month-to-month contracts.
* **Long-tenure customers** and those on **annual or two-year plans** exhibited significantly **lower churn rates**, likely due to stronger loyalty or contractual commitment.

**Recommendations to Mitigate Churn**

1. **Strengthen early engagement** by providing robust onboarding support and welcome offers to new customers.
2. **Promote long-term contracts** through discounts, exclusive benefits, or loyalty programs to lock in customer commitment.
3. **Use churn probabilities** from the model to create **targeted campaigns** aimed at retaining high-risk customers.
4. **Monitor customers with high charges**, as they may be more sensitive to perceived value and are more likely to churn without proactive service and support.

This predictive modeling stage transformed raw customer data into a strategic tool for churn mitigation. By identifying patterns and behaviors associated with churn, we provided data-driven insights that can help guide marketing, customer service, and retention efforts across the organization.