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**MASTER OF SCIENCE IN ELECTRICAL AND COMPUTER  
ENGINEERING - [MSECE]**

**04-638: PROGRAMMING FOR DATA ANALYTICS**

**TELCO CUSTOMER CHURN ANALYSIS: A REFLECTION**

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# Abstract

This project addressed the critical challenge of customer churn in telecommunications through advanced analytics and machine learning. The analysis combined unsupervised and supervised learning techniques to identify at-risk customers and develop targeted retention strategies, achieving high predictive accuracy (AUC > 0.96).

## 1. Solution Approach

### 1.1 Data Preprocessing & EDA

1. Identified bimodal tenure distribution (0-10 and 60-70 months)
2. Discovered strong correlation between tenure and total charges (0.82)
3. Found negative correlation between tenure and churn (-0.35)

### 1.2 Unsupervised Learning

1. Implemented K-means clustering
2. Used elbow method for optimal clusters
3. Applied t-SNE for dimensionality reduction

### 1.3 Supervised Learning

1. Split data: 70% training, 15% validation, 15% test
2. Implemented Logistic Regression, Random Forest, XGBoost
3. Addressed class imbalance using SMOTE
4. Evaluated using AUC-ROC, precision, recall, F1-score

### 1.4 Integration

1. Combined clustering with churn probabilities
2. Developed segment-specific strategies
3. Created visualization dashboard

## 2. Technical and Analytical Challenges

### 2.1 Data Processing Challenges

1. Bimodal distribution in tenure months (peaks at 0-10 and 60-70 months) required specialized handling
2. Complex feature correlations (Tenure-Total Charges: 0.82, Tenure-Churn: -0.35) demanded careful feature engineering

### 2.2 Modeling Challenges

1. Class imbalance in customer segments required SMOTE implementation
2. Feature selection complexity due to high correlation between certain variables

### **3. Ethical Considerations**

The project identified significant algorithmic bias risks:

1. Algorithm bias
2. Demographic disparities in predictions (e.g., higher churn rates for seniors)
3. Privacy concerns

### **4. Mitigation strategies**

1. Regular bias audits across demographic segments
2. Implementation of fairness-aware modeling techniques
3. Strict data privacy protocols

### **5. Future Improvements**

1. Development of real-time prediction capabilities
2. Enhanced feature engineering incorporating temporal patterns
3. Dashboard development
4. Automated intervention trigger system

### **Conclusion**

The integration of clustering with churn predictions enabled targeted retention strategies, offering a comprehensive solution to the telecommunications industry's churn challenges.

**END**