Automating Classification of Audio-Visual Content and Rating for Regulation and Personal Use

DSC-PT-10

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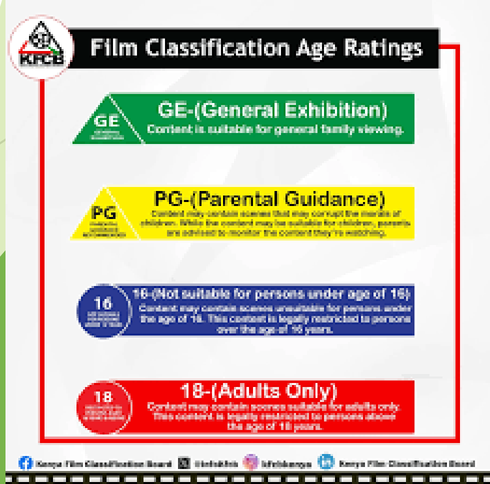

KFCB
GE
PG
16
18

Film Classification Age Ratings

GE-(General Exhibition)
Content is suitable for general family viewing.

PG-(Parental Guidance)
Content may contain scenes that may corrupt the morals of children. While the content may be suitable for children, parents are advised to monitor the content they're watching.

16-(Not suitable for persons under age of 16)
Content may contain scenes unsuitable for persons under the age of 16. This content is legally restricted to persons over the age of 16 years.

18-(Adults Only)
Content may contain scenes suitable for adults only. This content is legally restricted to persons above the age of 18 years.

Kenya Film Classification Board · @InfoKfcb · kfcbkenya · Kenya Film Classification Board

PROJECT OVERVIEW

- Develop a machine learning model to automate film classification based on genre, synopsis, platform, and other metadata.
- Enhance regulatory efficiency by providing intelligent rating suggestions aligned with Kenya’s classification guidelines.
- Support parental control tools and age-based content filtering for safer content consumption.
- Promote discoverability and categorization of local content to increase visibility of Kenyan productions.

Objectives

This project is aimed at assisting the regulator in automating the classification of audiovisual content in Kenya.

1. Automate film classification using machine learning to predict appropriate age ratings.
2. Improve regulatory efficiency by providing AI-based rating suggestions.
3. Support parental controls through age-based content filtering tools.
4. Promote and recommend local content through enhanced categorization and discoverability.

DATA USED

The data used for this project was collected by the Kenya Film Classification Board (KFCB) between July 2022 and June 2025.

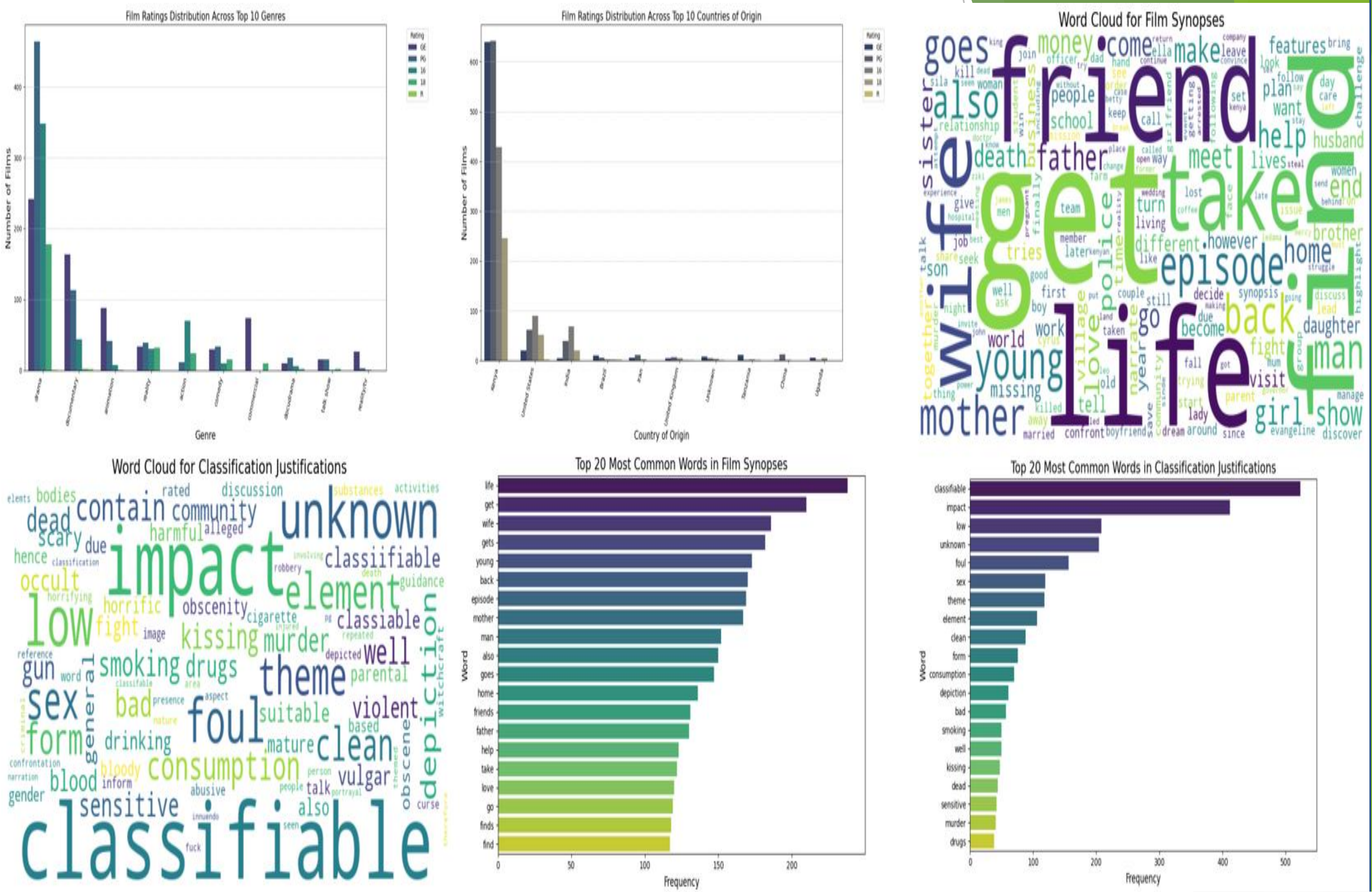
It was sourced from official classification records containing film metadata and regulatory decisions across different platforms (cinema, TV, online streaming).

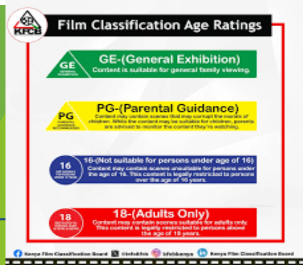
For purposes of this study, the data was consolidated and structured as follows:

A unified dataset comprising 2,574 film records with 15 key attributes, including film title, genre, classification, synopsis, rating, and origin.

The data was cleaned and standardized to support analysis of content patterns, classification trends, and audience suitability.

EDA Summary





KFCB

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MODELLING

Logistic Regression Model(Baseline)

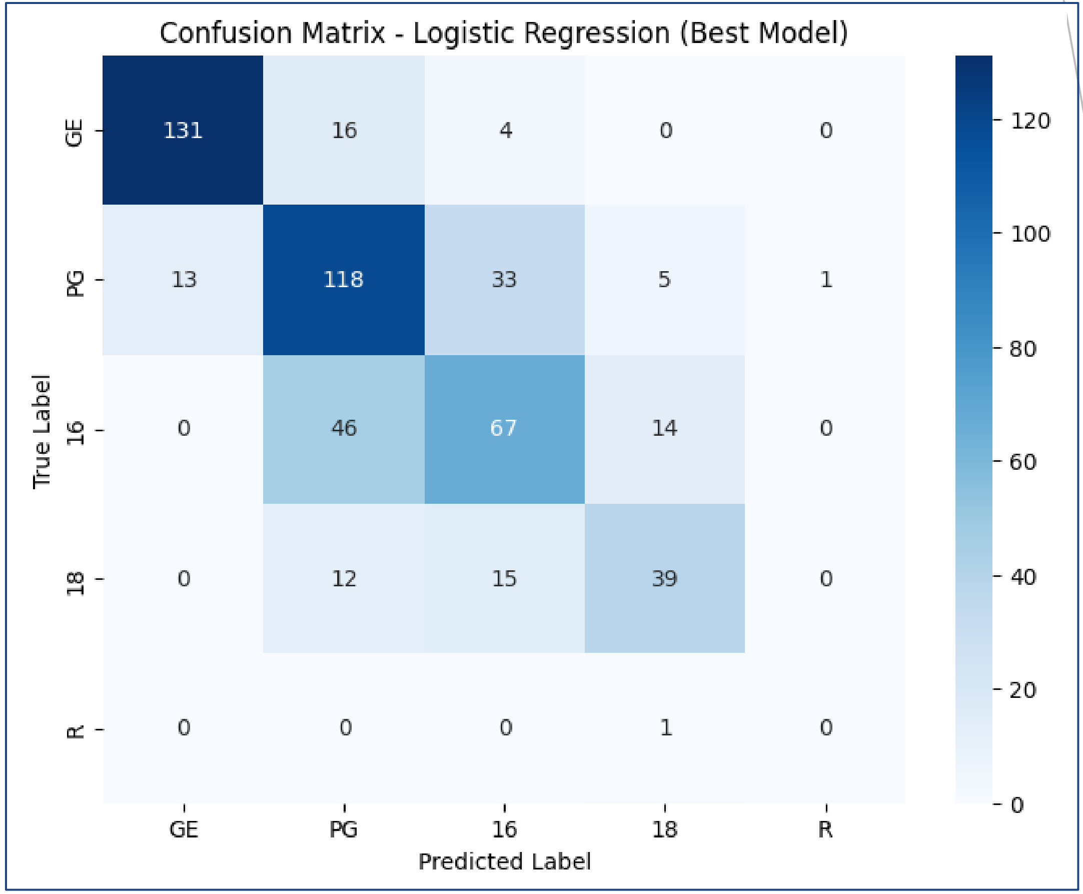
1. Logistic Regression

- **Best Parameters**: `C=1`, `solver='lbfgs'`

- **Accuracy**: 0.69

- **Best F1-Weighted Score (CV)**: 0.69

- **Notes**: Serves as a solid baseline with decent precision for 'GE' and 'PG' classes. Underperforms for rare classes like 'R'.



Confusion Matrix - Logistic Regression (Best Model)

True Label \ Predicted Label	GE	PG	16	18	R
GE	131	16	4	0	0
PG	13	118	33	5	1
16	0	46	67	14	0
18	0	12	15	39	0
R	0	0	0	1	0

- The model performs well in predicting GE ratings, with minimal misclassifications. However, PG, 16, and 18 show significant overlap many PG films are misclassified as 16, and vice versa suggesting feature similarity in borderline content. The model struggles to correctly classify Restricted films due to the very limited training data in that class. Improving class balance and incorporating more discriminative features could enhance overall rating accuracy.

MODELLING

XGBoost Classifier Best Model

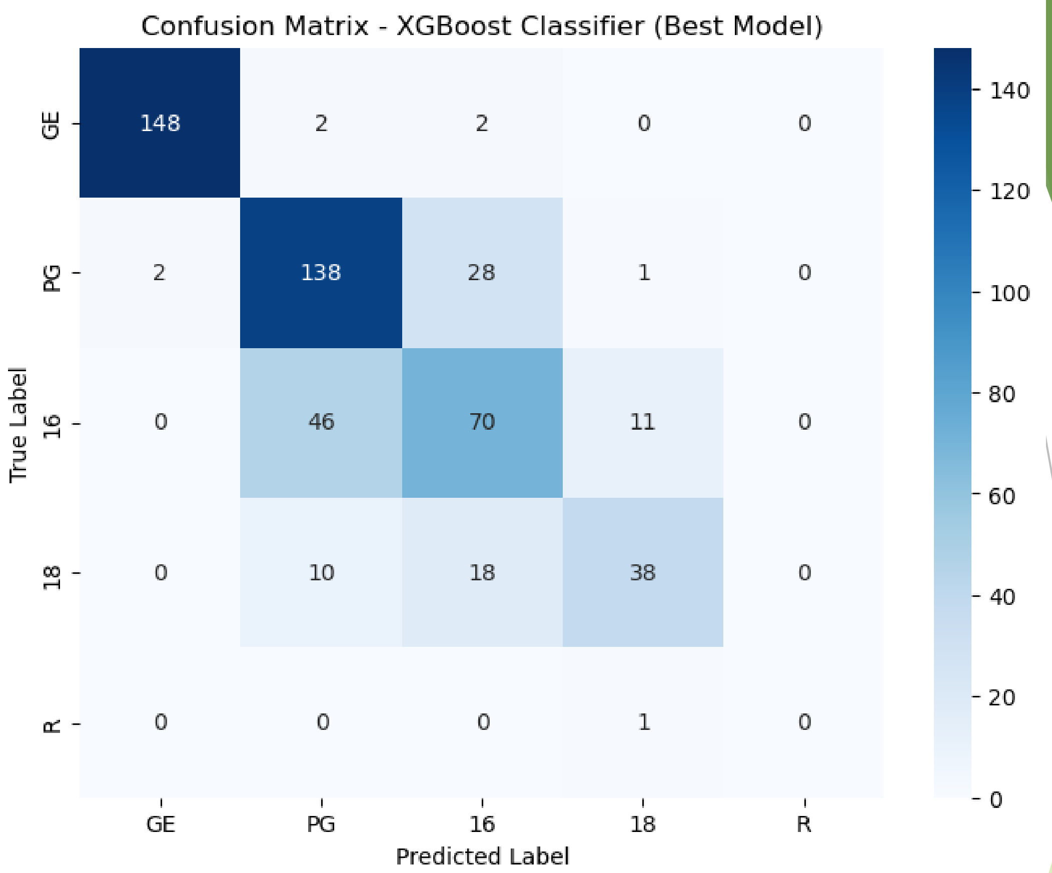
XGBoost Classifier

- Accuracy: **77.48%**

- F1-Weighted Score (Cross-Validation): **0.76**

- Excellent balance between performance and interpretability

- Robust against overfitting and handles both categorical and numerical features effectively



Confusion Matrix - XGBoost Classifier (Best Model)

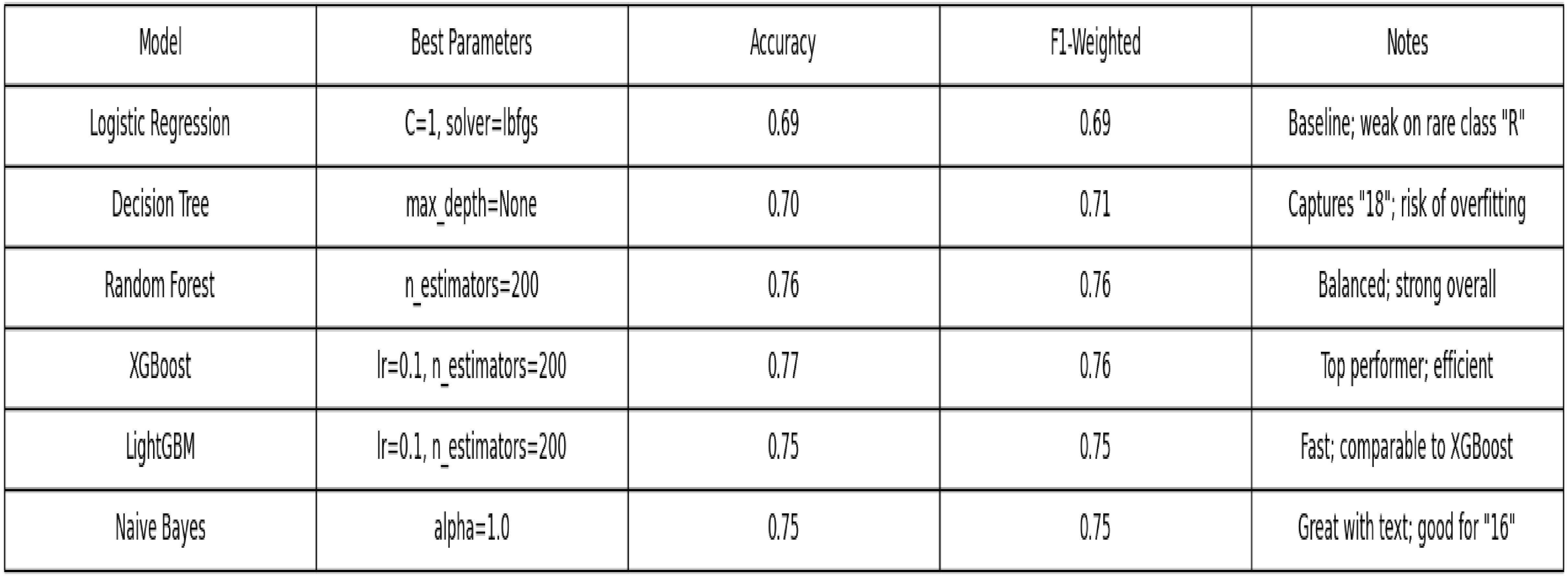
True Label \ Predicted Label	GE	PG	16	18	R
GE	148	2	2	0	0
PG	2	138	28	1	0
16	0	46	70	11	0
18	0	10	18	38	0
R	0	0	0	1	0

High True Positives across major classes like "PG" and "GE", indicating strong classification performance on the most frequent categories.

- **Misclassifications** are more common between similar or adjacent rating classes (e.g., "16" misclassified as "18"), suggesting overlap in content characteristics.

- The **"R" and "18" classes**, which are less represented, show slightly lower recall—typical in imbalanced datasets.

MODELS EVALUATION TABLE



Model	Best Parameters	Accuracy	F1-Weighted	Notes
Logistic Regression	C=1, solver=lbfgs	0.69	0.69	Baseline; weak on rare class "R"
Decision Tree	max_depth=None	0.70	0.71	Captures "18"; risk of overfitting
Random Forest	n_estimators=200	0.76	0.76	Balanced; strong overall
XGBoost	lr=0.1, n_estimators=200	0.77	0.76	Top performer; efficient
LightGBM	lr=0.1, n_estimators=200	0.75	0.75	Fast; comparable to XGBoost
Naive Bayes	alpha=1.0	0.75	0.75	Great with text; good for "16"

CONCLUSION

- Successfully built a machine learning model to classify films based on age-appropriateness using KFCB guidelines.
- XG Boost classifier performed best (Accuracy: **77.48%**, F1: **0.772**).
- Text features like synopses and justifications were key in improving prediction.
- EDA revealed rating patterns across genres, platforms, and countries.
- The solution supports regulators, parents, and content platforms in faster, scalable, and objective classification.

Project Challenges

- **Missing Data**: Key columns like VENUE and CONTACT had many null values.
- **Data Cleaning**: Inconsistent formats in fields like DURATION(MINS) required extensive preprocessing.
- **Class Imbalance**: Rare ratings like 'R' had very few samples, hurting model recall.
- **Similar Class Overlap**: Models confused PG, 16, and 18 due to feature similarity.
- **Text Feature Complexity**: High-dimensional TF-IDF features from SYNOPSIS increased model complexity.
- **Evaluation Limitation**: Low support for rare classes affected confusion matrix reliability.

RECOMMENDATIONS

•Use the ML model as a **pre-screening tool** for faster content review.
•**Integrate API** with KFCB or streaming platforms for real-time classification.
•Switch to **transformer models** (e.g., BERT) for better text analysis.
•Apply **SMOTE or class weighting** to handle rating imbalance.
•Add **human-in-the-loop** feedback to improve accuracy over time.
•Build a **parental control app** to help filter content by rating.
•Include **image/audio features** for richer content classification.
•Perform **regular audits** to detect and correct model bias.

Next Steps

Advanced NLP: Use BERT/RoBERTa for better text understanding
Multimodal: Add image/audio features
API & Dashboard: Deploy for real-time use
Bias Audit: Fix class imbalance, monitor fairness
Human Feedback: Improve model via user input
Scaling: Localize for other countries/languages

🙏 Thank You

Thank you for your time and attention.

We appreciate your support and interest in our project.

— *The Team*