High Recall Oriented Employee Attrition Prediction using Stacking Ensemble Model

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ABSTRACT

Understanding and predicting employee attrition has become essential for effective HR planning and talent retention strategies. In this study, we developed a stacking ensemble machine learning model optimized for high recall on the minority class (Attrition = 'Yes') using the IBM HR Analytics dataset. The dataset showed significant class imbalance (16:84), necessitating the use of SMOTE for synthetic oversampling. After rigorous preprocessing — including feature pruning, label encoding, and standard scaling — we trained base learners (Random Forest, XGBoost, LightGBM) and a meta learner (Extra Trees Classifier) with manually tuned hyperparameters for optimal performance.
To further enhance sensitivity, we applied threshold tuning (optimal at 0.28) to maximize F1-score for the minority class. The final model achieved a recall of 0.83 and an F1-score of 0.57 on the attrition class, significantly outperforming classical baselines.

METHODS

Preprocessing and handling Imbalance

1 RAW DATA

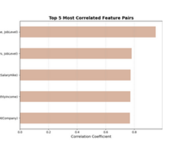
Starting point with original dataset features

- 35 features
- 1470 datapoints
- 16:84 class imbalance

2 Cleaning

Removed redundant features:

- EmployeeCount
- Over18
- StandardHours



MonthlyIncome and JobLevel showed high correlation (0.95), so MonthlyIncome was dropped

3 Encoding

Used Label encoding to convert Categorical features into numerical (eg: Gender, JobRole)

4 SMOTE

Since the dataset was quiet imbalanced, we applied SMOTE to balance the classes in the train data

5 Scaling

Used Standard Scaler to normalize numerical features

6 Model Input

Final processed data ready for model training

Input Dataset

Preprocessed HR data with balanced classes

Base Learners

Random Forest [n_estimators=120,max_depth=5,min_samples_split=10,min_samples_leaf=5,max_features='sqrt' ,bootstrap=True,classweight='balanced_subsample']

XGBoost [use_label_encoder=False,eval_metric='logloss',n_estimators=100,learning_rate=0.03,max_depth=3, subsample=0.6,colsample_bytree=0.6,scale_pos_weight=2,reg_lambda=10,reg_alpha=2,gamma=10]

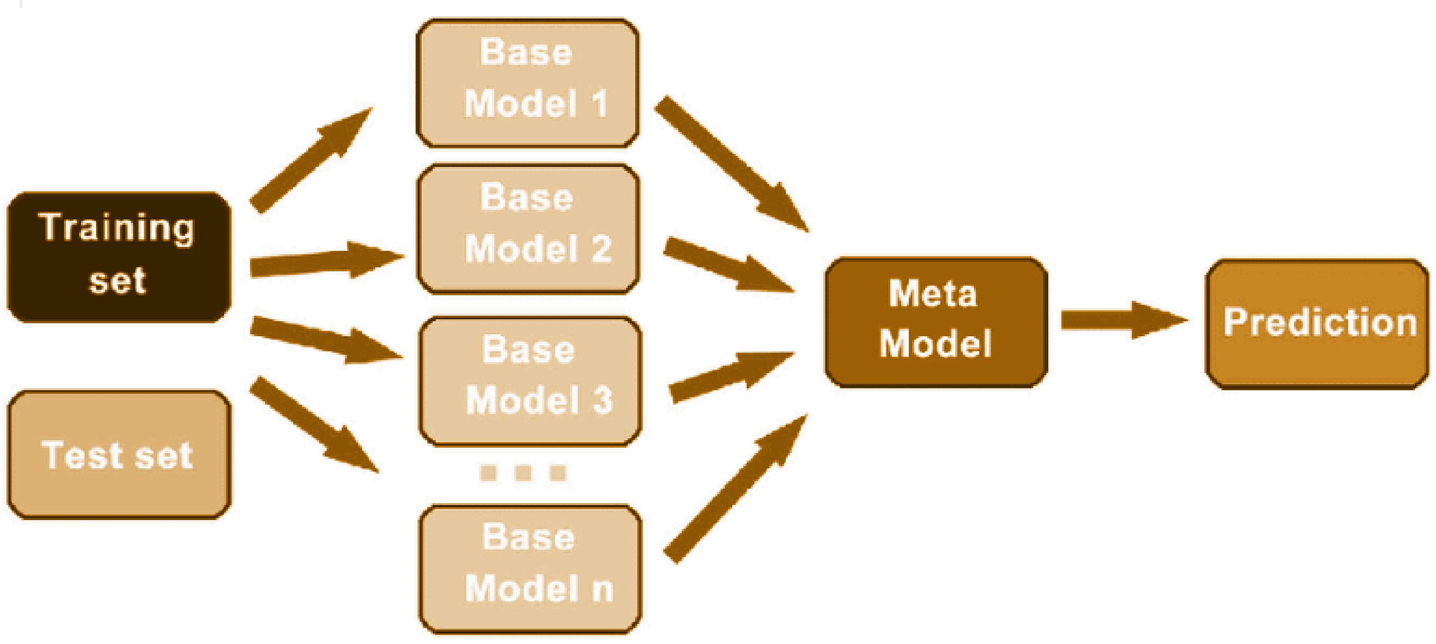
LightGBM [n_estimators=100,learning_rate=0.05,max_depth=5,subsample=0.7,colsample_bytree=0.7, class_weight='balanced',reg_lambda=5,reg_alpha=1]

Meta Learner

ExtraTrees Classifier [n_estimators=100,max_depth=6,min_samples_split=10,min_samples_leaf=5, max_features='sqrt',class_weight='balanced',n_jobs=-1]

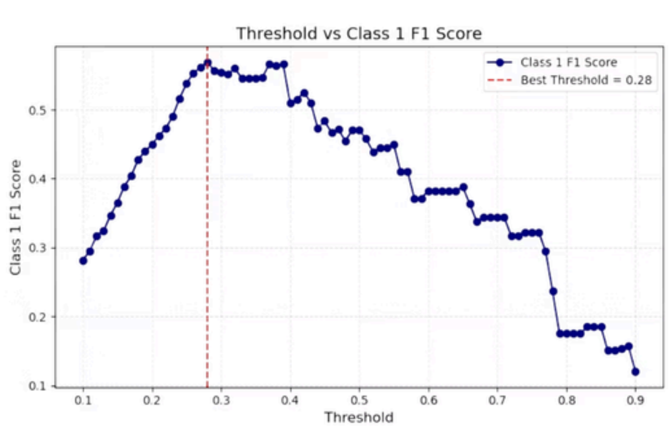
Combines predictions from base models

Final Prediction



Threshold Tuning & F1 Optimization

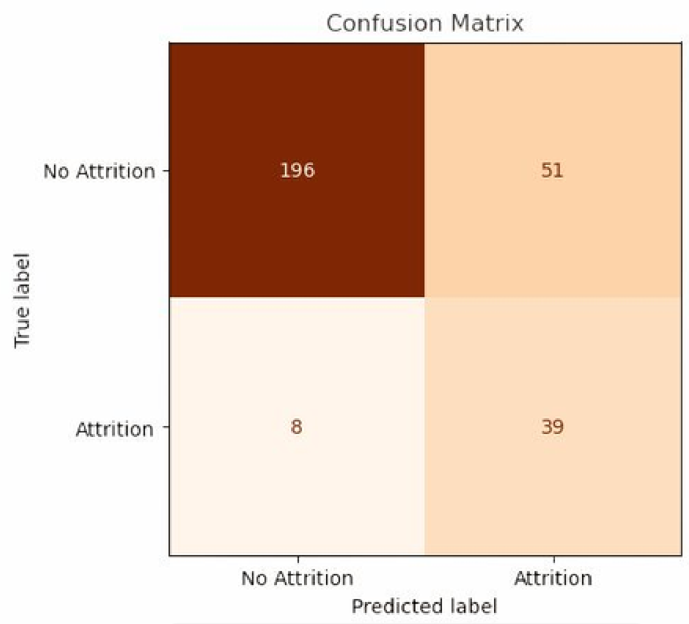
1. After training, we performed threshold tuning to optimize performance
2. Used model's predicted probabilities
3. Iterated threshold from **0.1** to **0.9** (step = 0.01)
4. Evaluated each on **class 1 F1-score**
5. Final selected threshold = 0.28
6. Helped improve **recall** and F1-score without retraining the model



Tuning the threshold allowed us to better balance false positives and false negatives, especially important for the minority class

RESULTS & CONCLUSION

Metric	Score
Accuracy	0.80
Precision	0.88
Recall	0.81
F1 score	0.83
Support	294
Recall (minority class)	**0.83**



High Recall of positive attrition cases (0.83) ensures most attrition cases are detected, aligning with our real-world objective of early identification & intervention.

Reference Study for SOTA: "Developing a hybrid machine learning model for employee turnover prediction: Integrating LightGBM and genetic algorithms" Hojat Talebi et al., Journal of Open Innovation: Technology, Market, and Complexity, Volume 11 (2025), Article ID: 100557 DOI: https://doi.org/10.1016/j.joitmc.2025.100557

Comparison with State-of-the-Art Model

It Uses GA for feature selection + LightGBM for classification

Performance Comparison

Proposed model outperforms SOTA across **all key metrics**

Ensemble Advantage

Stacking ensemble captures diverse learning patterns from RF, XGBoost & LGBM

Threshold Tuning

Additional threshold tuning improves recall (crucial for attrition prediction)

Metric	SOTA Model	Proposed Model
F1-Score	0.73	**0.83**
Precision	0.75	**0.88**
Recall	0.72	**0.81**
Accuracy	0.78	**0.80**

Cross-Dataset Validation

The model was tested on two additional datasets with different class balances and feature dimensions, to assess its generalization and recall consistency.

Dataset	Records	Features	Class Balance	Accuracy	Weighted Recall	Weighted F1-score
IBM	294	35	16:84	0.80	**0.81**	**0.83**
Watson	336	35	13:87	0.93	**0.93**	**0.93**
StealthTech	14,900	23	47:52	0.74	**0.74**	**0.74**

- High weighted metrics across all datasets show strong generalization
- Watson (Healthcare) dataset had **best overall metrics**, even with class imbalance
- Model adapts well to both **imbalanced** and **balanced** scenarios
- Reflects strong potential for real-world implementation across domains

Business Impact

- **High Recall = Early Identification of At-Risk Employees** → Even if few false positives exist, better to **consult** and **retain proactively**
- **Helps in flagging "Asset-Class" Employees** → Companies can't afford to lose top performers
- **Supports Strategic HR Decisions** → Personalized retention plans, counseling, incentive tweaking
- **Saves Cost of Rehiring & Retraining** → Retaining employees is cheaper than replacing them

Conclusion

High-Performance Predictor

Stacked ensemble model + **threshold tuning** creates a powerful attrition prediction system

Recall-Focused Strategy

Recall-focused approach aligns with modern HR priorities by catching all potential exits

Cross-Dataset Performance

Generalizes well across diverse datasets including corporate, healthcare, and synthetic environments

"Missing an attrition case can be costlier than wrongly flagging one"

so high recall gives the company that protective edge.

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