

A Novel Stacking Framework for Student Success Prediction Using Combined Machine Learning and Deep Learning Approaches



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Agenda

Presentation Outline

- Introduction and Background (3 slides)
- Contributions (2 slides)
- Literature Review (2 slides)
- Methodology (5 slides)
- Results and Analysis (6 slides)
- Conclusion and Future Work (2 slides)
- References (3 slides)

Total: 27 slides

INTRODUCTION AND BACKGROUND

INTRODUCTION

Why Student Success Prediction Matters

- Educational institutions must predict student achievement to make timely interventions and enhance academic results
- Traditional evaluation methods rely on post-exam results, limiting opportunities for effective support
- Early identification of at-risk students enables:
 - Personalized learning adjustments
 - Targeted academic support
 - Dropout prevention strategies
 - Resource allocation optimization

Current Challenges:

- Complex and diverse educational data (demographic, behavioral, attendance, psychometric)
- Difficulty isolating influential factors in academic outcomes
- Need for transparent, interpretable prediction models

INTRODUCTION AND BACKGROUND

PROBLEM CONTEXT & MOTIVATION

Single Model Limitations:

- Linear models: Cannot capture complex non-linear relationships
- Tree-based models: Prone to overfitting
- Neural networks: Lack interpretability
- Distance-based methods: Sensitive to noise and dimensionality

Why Stacking Framework?

- Combines strengths of multiple ML algorithms
- Reduces individual model weaknesses through ensemble learning
- Integrates ML and DL approaches for comprehensive pattern recognition
- Maintains interpretability through explainable AI techniques

Research Gap:

- Need for robust framework combining diverse algorithms
- Lack of comprehensive feature selection for educational data
- Limited integration of interpretability in ensemble methods

INTRODUCTION AND BACKGROUND

OBJECTIVES AND MOTIVATION

Primary Objectives

- Design intelligent prediction system leveraging ML and DL models in stacking ensemble
- Integrate comprehensive feature selection methods to identify influential academic factors
- Combine complementary model strengths through base learners and meta-learner architecture
- Enable data-driven interventions for early identification of at-risk students
- Ensure model interpretability using SHAP and LIME techniques

Expected Outcomes:

- Superior prediction accuracy compared to individual models
- Actionable insights for educational decision-making
- Scalable framework for diverse educational institutions

CONTRIBUTIONS

KEY RESEARCH CONTRIBUTIONS

Main Contributions

- Hybrid Feature Selection Technique
 - Combines filter methods (Pearson correlation, Chi-square, Mutual Information)
 - Integrates wrapper methods (recursive feature elimination)
 - Balances speed, interpretability, and predictive capability
- Comprehensive ML Base Learners
 - Linear/Ridge/Lasso Regression for linear relationships
 - Decision Tree/Random Forest for non-linear patterns
 - K-Nearest Neighbors for similarity-based predictions
- Advanced Meta-Learning Architecture
 - Multi-Layer Perceptron (MLP) meta-learner
 - Captures complex non-linear relationships
 - Optimizes ensemble predictions

CONTRIBUTIONS

ADDITIONAL CONTRIBUTIONS

Performance and Applications

- Superior Performance Achievement
 - Stacking ensemble: $R^2 = 0.8722$, $MSE = 17.3085$
 - Outperforms individual baseline models
 - Robust prediction across diverse student profiles
- Practical Educational Applications
 - Early identification of at-risk students
 - Data-driven intervention strategies
 - Support for personalized learning and dropout prevention

LITERATURE REVIEW

LITERATURE REVIEW - RECENT STUDIES

Identified Gaps and Our Solutions

Gap Category	Current Limitations	Our Solution
Model Integration	Single model approaches or limited ensemble	Comprehensive stacking: 6 ML + 1 DL
Feature Selection	Basic statistical or single-method selection	Hybrid filter + wrapper approach
Dataset Scope	Limited to specific platforms/institutions	80,000 student multi-dimensional dataset
Interpretability	Focus on accuracy without explanation	Integrated SHAP and LIME analysis
Performance Balance	High accuracy OR interpretability	Both high performance AND explainability
Application	Academic research without validation	Framework for educational intervention

LITERATURE REVIEW

LITERATURE REVIEW - RESEARCH GAPS

Comparative Analysis of Related Work

Study	Year	Dataset	Models	Best Results	Key Advantages
Wang & Yu [14]	2025	Online behavioral data	Logistic Regression + Taylor	Higher accuracy vs traditional	Lightweight, interpretable
Althaqafi et al. [15]	2025	xAPI-Edu-Data	Ensemble (Stacking + RF)	Precision = 0.83	Balanced classes, robust
Sandeepa & Mohottala [16]	2025	School dataset	MLPC, Decision Tree, SVM	MLPC: 86.46% accuracy	High accuracy, explainable
Yuan et al. [18]	2024	edX dataset	XGBoost + SHAP	Near perfect for autonomous learners	Personalized modeling
Arya et al. [19]	2024	UCI Portuguese	CNN-LSTM hybrid	98.45% accuracy	Spatial-temporal patterns
Ben Said et al. [21]	2024	OULAD	Dual-path CNN	92.7% accuracy	Novel time-series imaging

METHODOLOGY

DATASET DESCRIPTION

Comprehensive Student Dataset (80,000 Records)

Five Main Feature Categories:

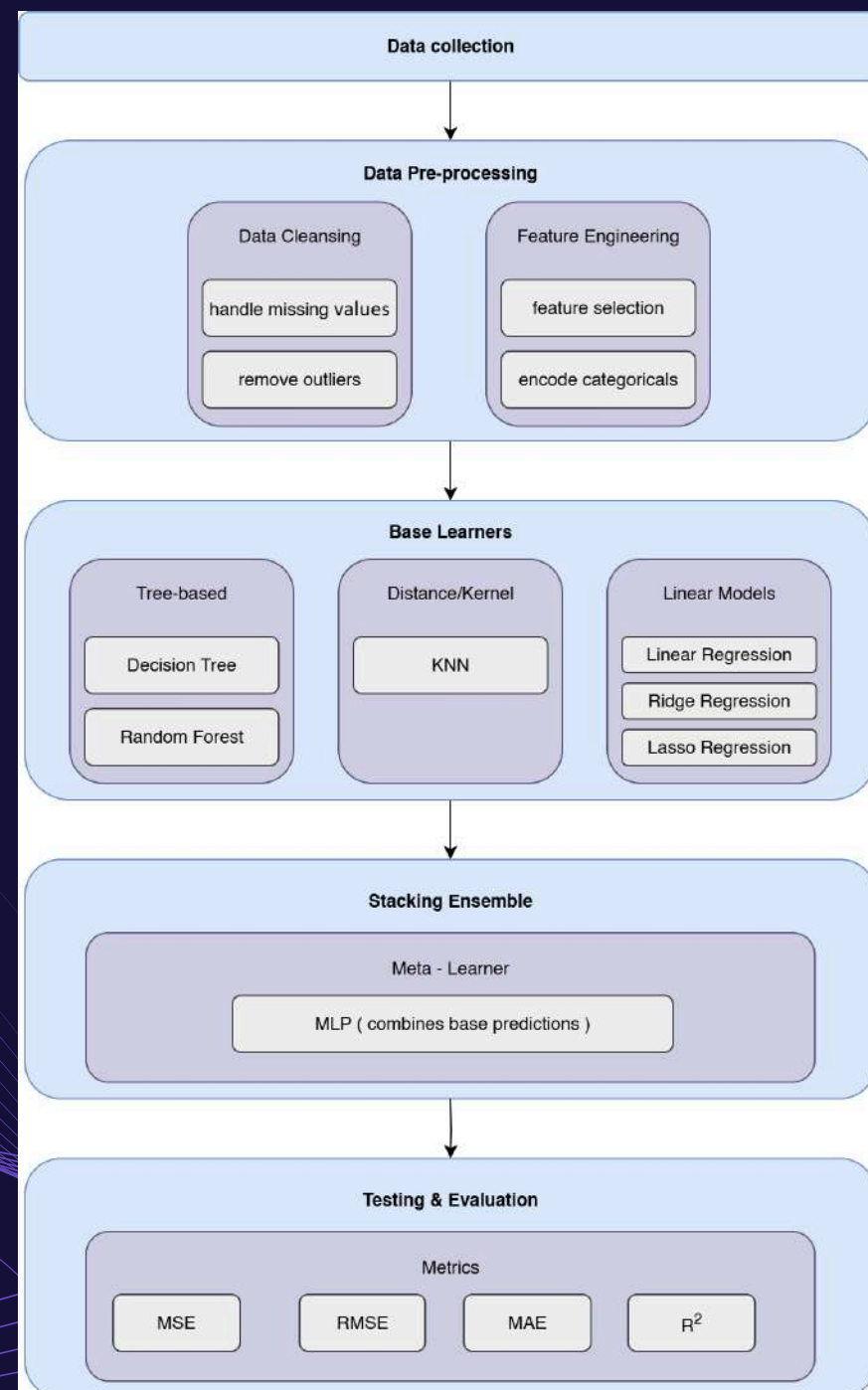
- Academic Information
 - Student ID, Age (16-28), Gender, Major
 - Study hours per day, Attendance percentage
 - Previous GPA, Exam scores
- Digital Lifestyle Factors
 - Social media hours, Netflix hours, Screen time
 - Modern technology impact on learning
- Physical & Mental Health
 - Sleep hours, Exercise frequency, Diet quality
 - Mental health rating, Stress level, Exam anxiety (1-10 scale)
- Family & Support Systems
 - Family income range, Parental support/education level
 - Access to tutoring, Extracurricular participation
- Personal Management
 - Motivation level, Time management score
 - Learning style, Study environment preferences

METHODOLOGY

PROPOSED FRAMEWORK ARCHITECTURE

Stacking Ensemble Framework Overview

Pipeline Flow:



Key Components:

- Input Layer: 80,000 students with multi-dimensional data
- Preprocessing: Data cleaning, scaling, encoding, feature engineering
- Feature Selection: Hybrid approach (Filter + Wrapper methods)
- Base Models: 6 diverse ML algorithms
- Meta-Learner: Multi-Layer Perceptron for optimization
- Output: Performance classification with interpretability

Benefits:

- Combines diverse learning approaches
- Maintains model interpretability
- Supports educational interventions

METHODOLOGY

FEATURE SELECTION PROCESS

Two-Phase Hybrid Selection Strategy

- Phase 1: Filter Methods
 - ·Chi-Square Test: Categorical variables (major, gender, learning style)
 - ·Pearson Correlation: Linear relationships with continuous variables
 - ·Mutual Information: Non-linear dependencies and complex interactions
 - ·Selection: Top 10 features from each method
- Phase 2: Wrapper Method
 - ·Recursive Feature Elimination: Uses LinearRegression as estimator
 - ·Performance-based evaluation: Direct contribution to accuracy
 - ·Cross-validation: Unbiased performance estimates
- Integration:
 - ·Union Operation: Combines all method selections
 - ·Comprehensive Coverage: Academic, lifestyle, psychological factors
 - ·Redundancy Analysis: Identifies overlapping features

METHODOLOGY

BASE MODELS ARCHITECTURE

Six Diverse ML Base Learners

Model Type	Algorithm	Strengths
Linear	Linear Regression	Interpretable, baseline
Regularized	Ridge Regression	Handles multicollinearity
Sparse	Lasso Regression	Feature selection
Non-linear	Decision Tree	Captures interactions
Ensemble	Random Forest	Robust predictions
Instance-based	K-Nearest Neighbors	Local patterns

Meta-Learner:

- Multi-Layer Perceptron (MLP)
- Dynamic weighting of base model predictions
- Non-linear optimization for final results

METHODOLOGY

EVALUATION METRICS

Comprehensive Performance Assessment

Regression Metrics:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$RMSE = \sqrt{MSE}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Educational Relevance:

- Performance categorization (High/Medium/Low)
- Intervention trigger thresholds

RESULTS AND ANALYSIS

EXPERIMENTAL SETUP

Two-Phase Hybrid Selection Strategy

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RESULTS AND ANALYSIS

EXPERIMENTAL DESIGN

Training and Validation Strategy

- Data Configuration:
 - Training Set: 80% (64,000 students)
 - Testing Set: 20% (16,000 students)
- Process Workflow:
 - Preprocessing Pipeline: Applied to training data
 - Feature Selection: Conducted on training set
 - Base Model Training: 6 ML algorithms independently
 - Meta-Learner Training: MLP on base predictions
 - Cross-Validation: 5-fold CV for robust estimation
- Optimization:
 - Grid Search: Systematic parameter exploration
 - Hyperparameter Tuning: Model-specific optimization

RESULTS AND ANALYSIS

INDIVIDUAL MODEL RESULTS

Base Model Performance Comparison

Model	MSE	RMSE	MAE	R ²	Rank
Linear Regression	17.5364	4.1877	3.1956	0.8705	4th
Ridge Regression	17.5364	4.1877	3.1956	0.8705	4th
Lasso Regression	17.5525	4.1896	3.2079	0.8704	6th
Decision Tree	17.414	4.173	3.2288	0.8714	3rd
Random Forest	17.3023	4.1596	3.2202	0.8722	1st
K-Nearest Neighbors	24.4988	4.9496	3.8094	0.819	7th

- Key Observations:
 - Random Forest: Best individual performance
 - Linear Models: Consistent baseline results
 - KNN: Struggled with high-dimensional complexity
 - Decision Tree: Good interpretability-performance balance

RESULTS AND ANALYSIS

STACKING FRAMEWORK RESULTS

Superior Ensemble Performance

- Stacked Model Achievement:
 - MSE: 17.3085 (↓ improvement from best individual)
 - RMSE: 4.1604 (↓ reduced error)
 - MAE: 3.2145 (competitive accuracy)
 - R²: 0.8722 (matches best individual)
- Performance Comparison:

Model	MSE Improvement	RMSE Improvement	R ² Change
vs Linear	-1.30%	-0.70%	0.17%
vs Ridge	-1.30%	-0.70%	0.17%
vs Decision Tree	-0.60%	-0.30%	0.08%
vs Random Forest	-0.01%	-0.02%	Tied
vs KNN	-29.40%	-15.90%	5.32%

- Key Achievement: Consistent performance with reduced variance

RESULTS AND ANALYSIS

FEATURE IMPORTANCE ANALYSIS

Top Contributing Features:

- Top Contributing Features:

Rank	Feature	Category	Impact	Educational Significance
1	Previous GPA	Academic	High +	Strong historical predictor
2	Study Hours/Day	Academic	High +	Direct effort correlation
3	Attendance %	Academic	High +	Participation importance
4	Mental Health Rating	Psychological	Moderate +	Well-being affects learning
5	Stress Level	Psychological	Moderate -	High stress impairs performance
6	Sleep Hours	Lifestyle	Moderate +	Rest quality impacts cognition
7	Motivation Level	Personal	Moderate +	Drive for success
8	Time Management	Personal	Moderate +	Organization skills

- Insights:
 - Academic factors most predictive
 - Lifestyle and psychological factors significant
 - Digital habits moderate influence

RESULTS AND ANALYSIS

DISCUSSION OF FINDINGS

Key Insights and Implications

- Model Performance:
 - Ensemble Benefit: Stacking achieves consistent high performance
 - Feature Hierarchy: Academic > Psychological > Lifestyle factors
 - Individual Variation: Meta-learner adapts to student profiles
 - Robustness: Multiple models reduce algorithm limitations
- Educational Significance:
 - Holistic Approach: Multiple factor categories matter
 - Early Warning: High R^2 enables reliable early prediction
 - Actionable Insights: SHAP/LIME provide intervention guidance
 - Personalization: Framework adapts to diverse student needs
- Practical Applications:
 - Resource Allocation: Targeted support distribution
 - Policy Development: Evidence-based educational strategies
 - Intervention Design: Specific factor-based support plans

CONCLUSION AND FUTURE WORK

CONCLUSION

Research Summary and Achievements

- Key Accomplishments:
 - Novel Framework: Successfully integrated ML and DL in stacking ensemble
 - Superior Performance: Achieved $R^2 = 0.8722$, matching best individual models
 - Comprehensive Analysis: 80,000 student records with multi-dimensional features
 - Enhanced Interpretability: SHAP and LIME for transparent predictions
- Research Impact:
 - Hybrid Feature Selection: Effective filter + wrapper methodology
 - Diverse Base Models: 6 ML algorithms capturing different patterns
 - Advanced Meta-Learning: MLP optimization of ensemble predictions
 - Practical Framework: Actionable insights for educational institutions
- Validation Results:
 - Framework demonstrates reliable prediction performance
 - Interpretability supports practical educational applications
 - Scalable methodology for diverse educational contexts

CONCLUSION AND FUTURE WORK

FUTURE WORK

Research Extensions and Improvements

- Technical Enhancements:
 - Advanced Architectures: Transformer-based meta-learners
 - Temporal Modeling: RNN/LSTM for longitudinal tracking
 - Multi-Modal Integration: Text-based feedback and behavioral patterns
 - Real-Time Prediction: Continuous student monitoring optimization
- Data and Application:
 - Longitudinal Studies: Multi-semester student tracking
 - Multi-Institutional: Cross-institutional validation
 - Cross-Cultural: Different educational system adaptation
 - LMS Integration: Real-world learning management system data
- Research Directions:
 - Causal Analysis: Beyond correlation to causation
 - Bias Mitigation: Fairness across diverse populations
 - Privacy Preservation: Federated learning approaches
 - Automated Interventions: AI-driven recommendation systems

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Thank You

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