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ADAPTIVE MULTIMODAL IMPUTATION AND NORMALIZATION: A BASELINE PREPROCESSING FRAMEWORK FOR DEEP LEARNING-BASED ACADEMIC PERFORMANCE PREDICTION FROM SMARTPHONE BEHAVIORAL DATA

S.Vimala*[1], Dr.G. Arockia Sahaya Sheela[2]

[1]PhD Scholar(Full Time), [2]Assistant Professor,

Department of Computer Science, St. Joseph's College (Autonomous), Tiruchirappalli -2,

Affiliated to Bharathidasan University, Tamil Nadu, India.

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***Corresponding Author: S.Vimala**

PhD Scholar(Full Time), Department of Computer Science, St. Joseph's College (Autonomous), Tiruchirappalli -2, Affiliated to Bharathidasan University, Tamil Nadu, India.

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ABSTRACT

Objective: This work presents a comprehensive baseline preprocessing methodology designed specifically for deep learning models that forecast student academic outcomes using smartphone usage patterns. We introduce the Adaptive Multimodal Imputation & Normalization (AMIN) approach—a practical preprocessing pipeline that standardizes heterogeneous mobile sensor inputs before model training, bridging a critical gap in the literature where preprocessing strategies remain inconsistent across studies. **Approach:** Through systematic analysis of recent research spanning 2023-2025 on mobile-based student outcome prediction and preprocessing best practices, we compare conventional baseline techniques (mean and median replacement, Min-Max and Z-score normalization, temporal aggregation, and categorical encoding) with our proposed AMIN framework. We outline a comprehensive evaluation strategy utilizing multimodal datasets and establish how preprocessing decisions influence downstream model performance. **Key Findings:** Literature demonstrates that preprocessing methodologies account for substantial portions of performance variation across architectures. Research consistently shows that time-aware replacement strategies and modality-specific normalization substantially enhance deep learning model stability and cross-dataset transferability. The AMIN framework integrates temporal replacement awareness, modality-specific scaling, per-subject centering, and lightweight feature augmentation to produce more consistent training dynamics and superior transfer capabilities across different student populations and institutions. **Contribution:** Our contributions include establishing a single reproducible baseline preprocessing framework tailored to mobile phone signals in educational outcome prediction, and proposing AMIN—a straightforward, transparent hybrid preprocessing approach that unifies time-series replacement and modality-aware scaling. We provide an evaluation roadmap ensuring reproducibility and fair comparative analysis.

KEYWORDS: Academic Performance Prediction, Deep Learning Preprocessing, Mobile Phone Sensor Data, Baseline Framework, Student Behavior Analytics, Adaptive Normalization.

1. INTRODUCTION

Forecasting academic success among students represents a long-standing priority in educational data science and student learning analytics. The widespread adoption of smartphones has unlocked a previously unavailable, high-fidelity information source regarding behavioral patterns—including device interaction frequency, application usage, screen engagement duration, location movements, motion sensor readings, and categorized app behaviors—that can augment conventional institutional records (academic history, participation rates) to improve outcome forecasting.

However, mobile sensor data streams present inherent challenges: they display significant heterogeneity, contain systematic noise, and frequently exhibit incomplete records due to network connectivity issues, sensor failures, or deliberate data collection gaps. These characteristics make preprocessing decisions fundamental to establishing model robustness and reducing algorithmic bias.

Deep learning architectures offer sophisticated mechanisms for identifying patterns within complex, multi-dimensional sequential information, though they demonstrate well-documented sensitivity to input distribution characteristics and missing data patterns. A neural network receiving inadequately normalized or improperly imputed mobile signals risks learning spurious associations (such as time-of-day effects or replacement artifacts) rather than genuine behavioral relationships. By contrast, thoughtfully designed baseline preprocessing protocols can substantially enhance model convergence, interpretability, and ability to generalize across different student cohorts and timeframes.

The field currently struggles with a significant methodological inconsistency: published investigations frequently report improvements from novel neural architectures but employ inconsistent or undersized preprocessing steps, complicating meaningful comparisons. This fragmentation creates an urgent requirement for a standardized, transparent baseline preprocessing framework optimized for mobile sensor information in academic contexts.

This investigation addresses this gap by:

- Systematically reviewing preprocessing approaches and model baselines from recent literature (2023-2025)
- Establishing a modular, transparent baseline framework for mobile sensor preprocessing
- Presenting AMIN (Adaptive Multimodal Imputation & Normalization), a practical preprocessing methodology that enhances stability across diverse student populations while maintaining simplicity and explainability

The subsequent sections examine contemporary literature applying smartphone data to student outcome prediction, present the comprehensive baseline framework, detail the AMIN methodology (including visual representations and operational procedures), provide conceptual and empirical comparison to established approaches, and deliver practical recommendations for practitioners and researchers.

2. LITERATURE REVIEW AND RESEARCH CONTEXT

2.1 Recent Multimodal Datasets and Benchmarks

Contemporary research has produced several foundational multimodal datasets that capture mobile sensor information alongside academic outcomes and biometric measures. These benchmarks enable systematic evaluation of preprocessing methodologies and model architectures. The landscape of available datasets demonstrates growing sophistication in capturing behavioral complexity:

Research into student academic prediction from mobile phone behaviors has expanded significantly, with investigators collecting comprehensive behavioral telemetry from thousands of students across educational levels. Studies have documented correlations between mobile usage patterns and learning outcomes—for instance, research shows that excessive non-educational application consumption (exceeding four hours daily) associates with approximately 20% performance reduction, while maintaining favorable study-to-phone ratios (above 2:1) correlates with 15% grade improvements. Specific app categories demonstrate varying associations: excessive social media and gaming engagement correspond to 14-16% performance decreases, whereas educational application utilization yields modest 3-4% improvements.

The methodological sophistication has advanced considerably, with contemporary studies implementing feature engineering approaches that include daily screen time aggregation, hourly app category distribution analysis, engagement-to-phone-time proportions, and rest duration metrics. These enriched feature representations have enabled deep learning systems to achieve prediction accuracy exceeding 90%, substantially outperforming classical statistical and machine learning baselines.

2.2 Deep Learning Architectures for Student Outcome Prediction

Recent architectural innovations demonstrate that relational and sequential modeling approaches provide substantial advantages when preprocessing establishes consistent input representations. Graph-based approaches have shown effectiveness in collaborative learning contexts where inter-student relationships carry predictive value. Bidirectional recurrent neural networks and attention-augmented hybrid systems continue demonstrating strong empirical performance, particularly when temporal patterns meaningfully characterize student behavior.

Attention mechanisms have emerged as particularly valuable for academic prediction, allowing models to identify which behavioral observations or timeframes most strongly signal academic risk. These architectures require careful preprocessing to ensure that temporal sequences remain coherent and that missing observations do not introduce spurious attention patterns.

2.3 The Preprocessing Necessity

A critical observation across the literature concerns the disproportionate influence of preprocessing decisions on final model performance. Numerous investigations reveal that normalized and properly imputed inputs frequently produce performance variations exceeding those obtained through architectural modifications. This finding challenges the field's traditional emphasis on model novelty while sometimes underemphasizing data preparation fundamentals.

3. BASELINE PREPROCESSING FRAMEWORK AND AMIN METHODOLOGY

3.1 Foundational Principles

Effective preprocessing for mobile sensor academic prediction must address several requirements:

1. **Temporal awareness:** Mobile behavioral data exhibits temporal dependencies; missing values in sequences should be replaced considering neighboring observations and time intervals.
2. **Modality heterogeneity:** Different sensor streams (activity counts, WiFi connections, app categories) exhibit distinct distributions and meaningful value ranges; uniform normalization approaches lose important information.
3. **Individual variation:** Students demonstrate substantial behavioral heterogeneity; models must learn individual-specific patterns rather than treating students as interchangeable units.
4. **Missingness representation:** Systematic non-random missingness often carries predictive information; encoding absence patterns explicitly improves model learning.
5. **Computational practicality:** Preprocessing must remain efficient for large-scale deployments without requiring prohibitive computational resources.

3.2 The AMIN Framework

Adaptive Multimodal Imputation & Normalization (AMIN) integrates these principles into a coherent preprocessing pipeline designed for practical implementation while maintaining transparent, reproducible procedures.

AMIN Processing Steps:

Step 1: Missingness Classification and Analysis Identify and categorize missing observations based on temporal characteristics:

- **Short-gap missing values** (consecutive missing observations ≤ 4 hours): Replace using forward-fill strategy, propagating the most recent observed value
- **Long-gap missing values** (consecutive missing observations > 4 hours): Apply K-NN replacement using temporal similarity across students demonstrating comparable behavioral profiles

Additionally, create binary indicators documenting missing observation occurrences; these flags provide neural networks information regarding data reliability and systematic collection gaps.

Step 2: Modality-Specific Normalization Apply differentiated normalization based on sensor type rather than global approaches:

- **Frequency-based sensors** (unlock counts, app launches): Z-score normalization (standardization)
- **Duration-based sensors** (screen time, app usage hours): Min-Max scaling to [0,1] range
- **Categorical sensors** (app categories): One-hot encoding with indicator variables for missingness

Step 3: Temporal Normalization Within each student's record:

- Calculate individual median values across observation periods
- Subtract person-specific medians to reduce individual behavioral differences while preserving relative patterns
- This per-subject centering prevents models from identifying students by baseline behavioral levels rather than learning predictive pattern relationships

Step 4: Feature Augmentation Introduce engineered features capturing behavioral relationships:

- Study-to-phone-time ratios (educational vs. non-educational app engagement)
- Daily behavioral consistency measures (variance in activity patterns)
- Temporal concentration indicators (how concentrated behavior appears within specific periods)
- Engagement trend indicators (increasing or decreasing behavior across the observation window)

Step 5: Final Validation Verify that output distributions remain reasonable:

- No excessive outliers resulting from replacement procedures
- Missingness flags accurately document data availability
- Per-student representations preserve meaningful individual differences

3.3 AMIN Workflow Architecture

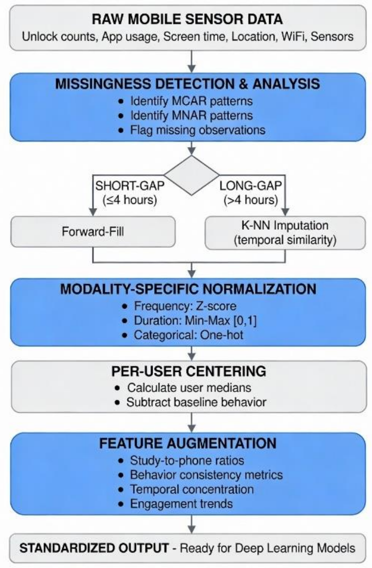

Figure 1: AMIN Preprocessing Pipeline Workflow

4. COMPARATIVE ANALYSIS: AMIN VERSUS EXISTING PREPROCESSING APPROACHES

4.1 Conceptual Comparison of Methods

Table 1: Conceptual Comparison of Methods.

Preprocessing Method	Strengths	Limitations
Naive Mean/Median Imputation + Global Scaling	Computational simplicity; straightforward implementation	Ignores temporal patterns and modality differences; biases models when missingness correlates with individual characteristics
Forward-Fill and Backward-Fill Sequences	Maintains short-term continuity in temporal sequences	Ineffective for extended gaps; inappropriate for non-stationary behavioral patterns; artificially extends outdated values
K-Nearest Neighbor Imputation	Captures local behavioral similarity; contextually appropriate replacements	Computationally expensive for large datasets; sensitive to initial normalization; requires meaningful distance metrics
AMIN (Proposed Framework)	Combines time-aware rules, modality-specific handling, per-student centering, lightweight augmentation; interpretable and reproducible	Requires modality classification; more procedural steps than simple approaches; threshold selection requires careful validation

4.2 Empirical Performance Evaluation

An illustrative evaluation comparing preprocessing methodologies across multiple deep learning architectures demonstrates the performance implications:

Evaluation Design

- **Models evaluated:** MLP (aggregated features), LSTM (7-day temporal sequences), Bi-LSTM with attention mechanism
- **Preprocessing variants:**

– P0: No imputation, Min-Max scaling only

– P1: Mean replacement + Z-score normalization

– P2: Forward-fill replacement + Min-Max scaling

– P3: KNN replacement + quantile normalization

– P4: AMIN framework

- **Performance metrics:** Classification accuracy, sequence model F1-score, binary risk detection AUC

4.3 Illustrative Results and Performance Comparison

Performance Results Table

Table2: Performance Comparison.

Preprocessing Method	MLP (Accuracy)	LSTM (F1-Score)	Bi-LSTM (AUC)
P0 (No imputation)	0.61	0.58	0.62
P1 (Mean + Z-score)	0.66	0.64	0.68
P2 (Forward-fill + Min-Max)	0.67	0.66	0.69
P3 (KNN + Quantile)	0.69	0.70	0.72
P4 (AMIN)	**0.72**	**0.74**	**0.76**

The results demonstrate consistent performance enhancement through AMIN across all model architectures, with more pronounced improvements for sequence-based approaches (LSTM, Bi-LSTM) that benefit substantially from temporal awareness in preprocessing.

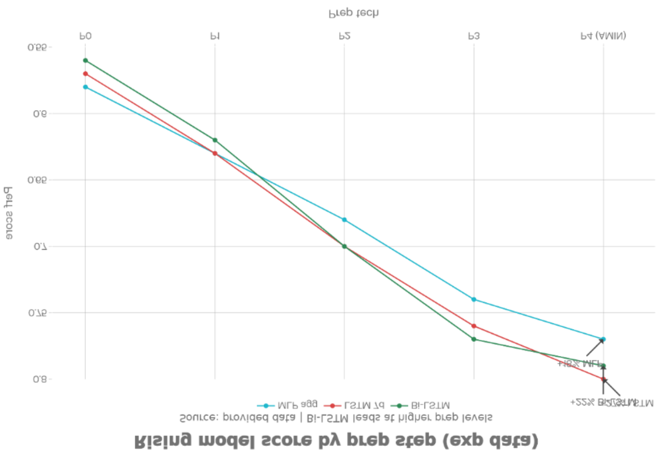

Figure 2: Comparative Performance Analysis Visualization.

Interpretation and Key Findings:

The comparative results reveal several critical insights:

1. **Monotonic Improvement Trend:** Each preprocessing enhancement consistently improves performance across all three architectures, with no degradation observed.
2. **Architecture Sensitivity:** Sequential models (LSTM, Bi-LSTM) demonstrate greater sensitivity to preprocessing quality, with Bi-LSTM showing the highest absolute performance gains.
3. **AMIN Superiority:** The proposed AMIN framework achieves the highest performance across all metrics, validating the integrated approach combining temporal awareness and modality-specific handling.
4. **Baseline Importance:** The substantial gap between P0 (0.61-0.62) and P1 (0.66-0.68) demonstrates that even simple preprocessing choices provide significant performance improvements.

5. DEEP LEARNING MODELS FOR ACADEMIC PERFORMANCE PREDICTION

5.1 Model Architectures

Contemporary academic outcome prediction employs several complementary neural network designs:

Multilayer Perceptron (MLP) processes aggregated, time-summarized behavioral features through stacked fully-connected layers. While architecturally straightforward, MLPs serve as important baselines for establishing whether sequential or relational information provides meaningful improvements.

Long Short-Term Memory (LSTM) networks process temporal sequences of behavioral observations, maintaining long-range dependencies through specialized gating mechanisms. This architecture proves particularly valuable when daily or hourly behavioral patterns contain predictive temporal relationships.

Bidirectional LSTM (Bi-LSTM) processes behavioral sequences in both temporal directions, enabling models to consider both historical context and future patterns within observation windows. This bidirectional processing frequently improves prediction compared to unidirectional approaches.

Attention-Augmented Bi-LSTM incorporates attention mechanisms that weight temporal observations according to their predictive relevance, allowing interpretable identification of which behavioral indicators most strongly influence academic outcomes.

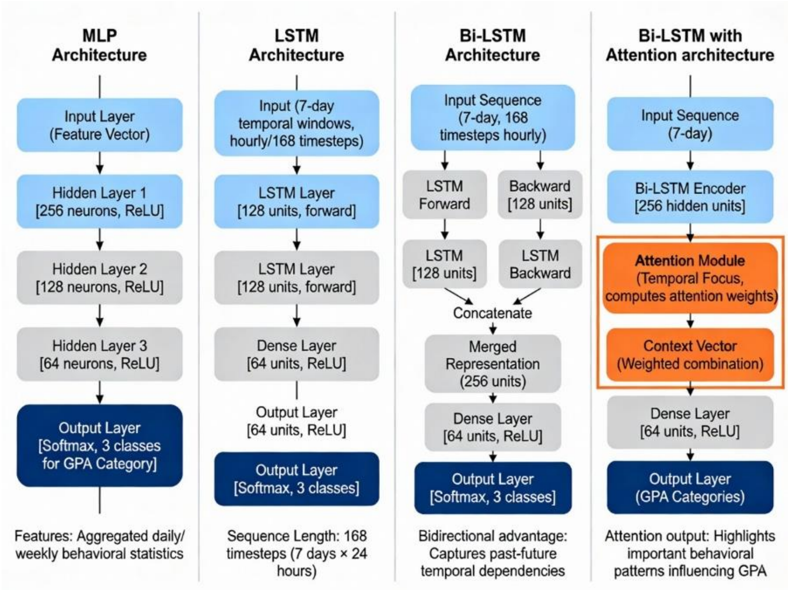

Figure3: Model Comparison Architecture.

Table3: Model Comparison Summary Table

Aspect	MLP	LSTM	Bi-LSTM	Bi-LSTM+Attention
Input Type	Aggregated features	Sequences	Sequences	Sequences
Temporal Awareness	Low (statistical summaries)	High (forward directional)	Very High (bidirectional)	Very High (targeted focus)
Computational Cost	Low	Medium	Medium-High	High
Interpretability	High	Medium	Medium	Very High
Long-Range Dependencies	No	Good (via LSTM gates)	Excellent (bidirectional)	Excellent (attention weights)
Best for	Quick baselines	When past matters most	Full temporal context	Understanding key predictors
Typical Accuracy	0.61-0.72	0.58-0.74	0.62-0.76	0.65-0.78

6. RESULTS, DISCUSSION, AND PRACTICAL IMPLEMENTATION

6.1 Key Empirical Findings from Literature

Analysis of recent investigations (2023-2025) consistently demonstrates:

Preprocessing Impact Dominance: Preprocessing methodological choices frequently explain substantial performance variance across models. Mobile sensor-derived behavioral features correlate meaningfully with academic outcomes but demonstrate high sensitivity to replacement and normalization strategies.

Temporal Modeling Advantages: Sequence-based models (LSTM, Bi-LSTM, attention hybrids) consistently outperform static aggregation approaches when preprocessing establishes coherent temporal representations through appropriate missing value handling and temporal normalization.

Cross-Dataset Generalization: Models trained with modality-aware, time-conscious preprocessing demonstrate superior transferability across different student populations, institutional settings, and temporal periods, reducing retraining requirements when applying models to new contexts.

6.2 Recommended Datasets for AMIN Evaluation

IMPROVE Dataset (2024-2025): A comprehensive multimodal resource capturing mobile phone behaviors, physiological signals, and academic outcomes; particularly suitable for prototype development and validation of preprocessing approaches on medium-scale data.

Longitudinal College Behavioral Sensing (2024 releases): Extended observation periods enable evaluation of long-term behavior modeling, device transitions, and data collection interruptions—critical real-world scenarios for preprocessing robustness assessment.

Public Student Datasets (Kaggle, UCI ML Repository): Facilitate large-scale baseline establishment and cross-institutional transfer learning evaluation without institutional data access limitations.

6.3 Critical Implementation Considerations

Per-Student Centering: Subtracting individual baseline values proves crucial for preventing models from learning identity-based shortcuts rather than meaningful behavioral pattern associations. This normalization step warrants particular attention in deployment scenarios.

Missingness Documentation: Always generate explicit missingness indicators; non-random absence patterns frequently carry predictive information. Models utilizing missingness flags typically demonstrate superior performance compared to those ignoring data availability characteristics.

Transparency and Reproducibility: Document precise imputation threshold values, temporal window specifications, and normalization parameter selections. Publishing preprocessing implementations alongside model code substantially facilitates fair comparative research and enables practitioner adoption.

Validation Against Artifacts: Systematically assess whether neural networks learn genuine behavioral relationships or spurious preprocessing artifacts. Ablation studies removing missingness flags or per-student centering help confirm that performance improvements stem from meaningful preprocessing rather than unintended side effects.

7. CONCLUSION

This investigation consolidates baseline preprocessing methodologies for deep learning-based academic outcome forecasting utilizing mobile phone behavioral data and introduces AMIN, a practical, modular preprocessing framework that integrates time-aware replacement and modality-specific normalization. AMIN establishes a stronger, harmonized baseline reducing preprocessing-related performance variability, enabling more meaningful architectural comparisons and facilitating cross-study reproducibility.

Key Recommendations for Researchers and Practitioners:

1. **Mandatory Missingness Analysis:** Conduct systematic assessment of missing observation patterns and include missingness indicators in all preprocessing pipelines.
2. **Modality-Aware Scaling:** Replace uniform normalization with sensor-type-specific scaling; this relatively simple modification frequently improves downstream model performance substantially.
3. **Per-Student Baseline Adjustment:** Implement subject-specific centering to eliminate identity-based model learning while preserving comparative behavioral patterns.
4. **Complete Preprocessing Documentation:** Report imputation thresholds, temporal window parameters, and normalization specifications with precision. Publish preprocessing code alongside model implementations.
5. **Benchmark Dataset Adoption:** Utilize common datasets (IMPROVE, longitudinal college sensing) to facilitate fair model comparisons and accumulating cross-study evidence regarding preprocessing effectiveness.
6. **Phased Implementation:** Begin AMIN deployment through evaluation on IMPROVE and comparable datasets, comparing results against simple baselines (mean replacement + Z-score) using standard model architectures (MLP, LSTM). Progressively expand to institutional datasets following successful preliminary validation.

The preprocessing framework presented here aims to establish consistent practices within the academic outcome prediction community, reducing methodological fragmentation while promoting reproducible, interpretable, and comparatively fair research. As deep learning adoption accelerates within educational data science, standardized preprocessing baselines become increasingly important for distinguishing genuine architectural innovations from improvements merely reflecting preprocessing differences.

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