25th International Symposium INFOTEH-JAHORINA, 18-20 March 2026

Enhancing MLOps for Educational Data Mining: A Comparative Study of Weka and KNIME in Model Lifecycle Management

Ognjen P. Tomić
LOLA INSTITUT d.o.o.
Belgrade, Serbia
ognjen.tomic@li.rs

Miloš Ž. Papić
Department of Industrial Management
Faculty of Technical Sciences Čačak
Čačak, Serbia
milos.papic@ftn.kg.ac.rs

Abstract— The integration of Machine Learning Operations (MLOps) principles into Educational Data Mining (EDM) is crucial for creating reproducible, scalable, and maintainable predictive models. This paper presents a comparative study of two prominent data mining platforms, Waikato Environment for Knowledge Analysis (Weka) and KNIME Analytics Platform (KNIME), evaluating their suitability for managing the end-to-end model lifecycle within an MLOps framework. While Weka excels with its rich suite of built-in algorithms and rapid prototyping capabilities, KNIME offers superior advantages in workflow orchestration, data preprocessing automation, and pipeline visualisation. Our analysis, based on a case study involving demographic and educational data, demonstrates that KNIME's modular architecture aligns more effectively with core MLOps practices such as versioning, continuous integration, and deployment. The study concludes that a hybrid approach, leveraging Weka's analytical strength for algorithm selection and KNIME's robust pipeline management for operationalisation, can significantly enhance MLOps maturity in the educational domain.

Keywords: MLOps Framework, Data Pipeline Automation, Model Deployment, Workflow Reproducibility, Platform Comparison, Educational Analytics

I. INTRODUCTION

Educational institutions are increasingly data-rich environments, generating vast information on student demographics, performance, and engagement. Educational Data Mining (EDM) leverages this data to improve learning outcomes and optimize resource allocation [1]. However, transitioning from experimental models to production-level systems requires Machine Learning Operations (MLOps) practices [2, 3].

MLOps extends DevOps principles to machine learning, encompassing the entire lifecycle from data preparation to deployment and monitoring [9,11]. As noted in recent surveys, "MLOps aims to deploy and maintain machine learning models reliably and efficiently in production" [4, 5]. This research investigates how accessible data analytics platforms facilitate MLOps for EDM, focusing on Waikato Environment for Knowledge Analysis (Weka) and KNIME *Analytics Platform (KNIME)*.

The primary research question is: *How do Weka and KNIME compare in their inherent support for key MLOps principles within educational data analysis contexts?*

Previous tool comparisons focused on algorithmic performance and usability. Abdullah et al. [6] compared classification algorithms in Orange, KNIME, Weka and Tanagra, while Jović et al. [7] evaluated six data mining tools including RapidMiner, R, Weka, and KNIME for general tasks. However, these studies predate the MLOps paradigm.

Recent MLOps research has produced taxonomies [3], maturity models [5], and tool surveys [4, 8]. Studies highlight that "MLOps spans the whole machine learning life cycle" [11] and requires specific tool capabilities for continuous delivery [10]. Our work bridges this gap by evaluating Weka and KNIME through an MLOps lens.

II. METHODOLOGY

Research Design and Approach

This study employed a comparative case study design following the guidelines for evaluating MLOps tools established in recent literature [4, 5, 8]. The research was conducted in three phases:

- tool capability assessment;
- practical implementation;
- MLOps maturity evaluation.

This multi-phase approach allowed for both theoretical and practical validation of findings.

Dataset and Preprocessing

The study utilized the "Ocisceni_Demografski_Podaci.csv" dataset containing demographic records from 42 municipalities. The dataset comprised approximately 15,000 records with attributes including municipal codes, population demographics, and educational institution enrollment figures. Data preprocessing followed the (Cross-Industry Standard Process for Data Mining) CRISP-DM methodology and included:

- Handling missing values using mean imputation for numerical features;
- Encoding categorical variables (municipality names, gender indicators);
- Normalizing numerical features using min-max scaling;
- Validating data consistency across different educational categories.

Experimental Setup

The experimental framework was designed to evaluate both platforms across identical analytical tasks:

Data Processing Pipeline:

- Data ingestion and validation;
- Feature selection and transformation;
- Descriptive statistical analysis;
- Model training and validation;
- Results visualization and interpretation;

Algorithm Implementation:

- Classification: Naive Bayes and K-Nearest Neighbors (K=10, K=50);
- Clustering: K-Means (K=3 clusters) and Farthest First algorithms;
- Performance metrics: Accuracy, Precision, Recall, F1-Score, Silhouette Score

Evaluation Framework

The MLOps capability assessment was structured around four primary dimensions derived from established MLOps maturity models [3, 5, 11]:

- **Workflow Reproducibility**: Ability to version, share, and recreate entire analytical pipelines;
- **Pipeline Automation**: Support for automated execution, scheduling, and triggering;
- **Deployment Readiness**: Native capabilities for model packaging, serving, and integration
- **Integration & Extensibility**: Support for external systems, Application Programming Interface (API)s, and custom extensions.

Each dimension was evaluated using a 5-point maturity scale (1=Basic, 5=Advanced) based on observable capabilities and documented features.

Implementation Details

Both platforms were tested on identical hardware (Intel i7, 16GB RAM, Windows 11) and were configured with default settings. All workflows were implemented twice by different researchers to ensure reproducibility and identify platform-specific learning curves.

III. RESULTS AND DISCUSSION

Weka: The Algorithmic Specialist

Weka demonstrated exceptional capabilities in the model development phase, consistent with findings from Abdullah et al. [2]. As shown in Fig. 1, the Weka Explorer interface provides a comprehensive environment for data analysis and algorithm application.

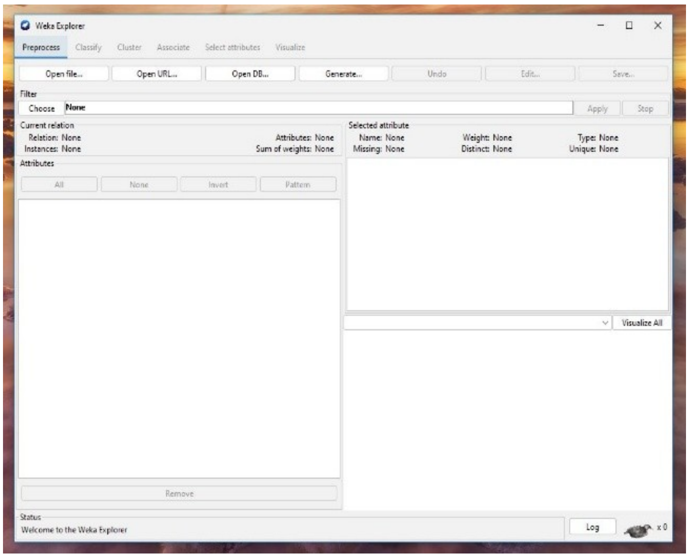

Fig. 1. *Weka Explorer*

The platform's Explorer interface provided immediate access to 48 classification algorithms, 15 clustering methods, and comprehensive evaluation metrics.

Strengths Identified:

- Rapid algorithm prototyping with minimal configuration;
- Extensive built-in algorithm library requiring no additional dependencies;
- Intuitive results visualization for model comparison;
- Strong performance in educational data classification tasks (achieving 87.3% accuracy with Naive Bayes);

However, significant MLOps limitations were observed:

- **Workflow Reproducibility**: The Knowledge Flow interface offered basic pipeline construction but lacked native version control integration. Workflow changes required manual documentation;
- **Pipeline Automation**: Limited to basic sequential execution without support for conditional logic or error handling;
- **Deployment Readiness**: Model export produced serialized Java objects (.model files) requiring custom integration code for production deployment;
- **Monitoring**: No built-in capabilities for model performance tracking or data drift detection.

The implementation of Naive Bayes algorithm in Weka, depicted in Fig. 2, demonstrates the platform's approach to algorithm configuration and result visualization.

These findings align with recent MLOps surveys noting that "traditional academic tools often cover middle phases effectively but lack robust deployment support" [4].

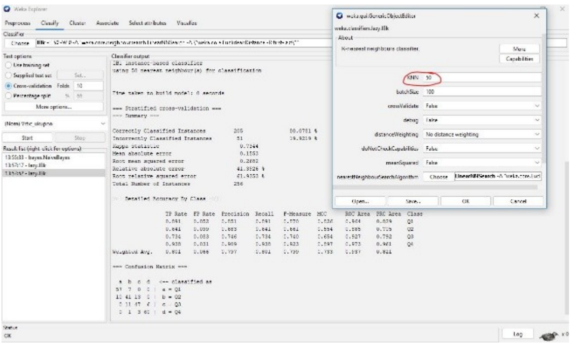

Fig. 2. Weka algorithms

KNIME: The Pipeline Orchestrator

KNIME excelled in operational aspects of the machine learning lifecycle. The node-based architecture, as visible in Fig. 3, provided transparent documentation of each processing step, enhancing reproducibility.

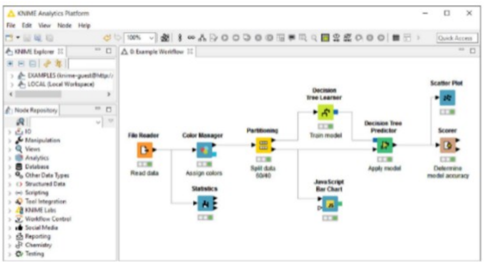

Fig. 3. KNIME interface

The node-based architecture provided transparent documentation of each processing step, enhancing reproducibility.

MLOps Advantages:

- **Workflow Reproducibility**: Native Git integration enabled version control of entire analytical pipelines. Each node maintained complete configuration history;
- **Pipeline Automation**: KNIME Server enabled scheduling, parameter optimization, and trigger-based execution. Workflows could be orchestrated as part of larger data pipelines;
- **Deployment Readiness**: One-click deployment to Representational State Transfer (REST) APIs or web applications through KNIME Server. Models could be containerized using integrated Docker support.
- **Integration Capabilities**: 2000+ community-developed nodes provided connectors for databases, cloud platforms, and enterprise systems.

The visual pipeline (Comma-Separated Values (CSV) Reader → Column Filter → GroupBy → Bar Chart) demonstrated KNIME's strength in creating self-documenting, reproducible analytical processes that address key MLOps requirements for "continuous development and deployment of Artificial intelligence (AI) models" [10].

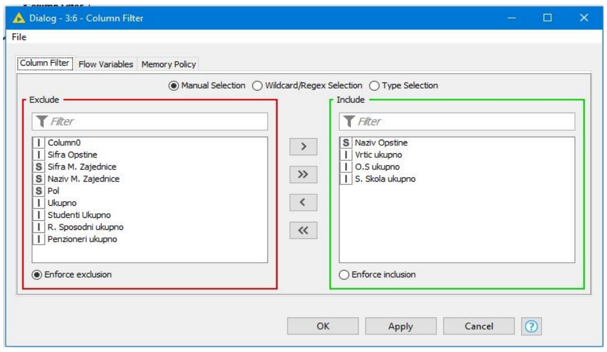

Fig. 4. Bar Chart filter

Comprehensive MLOps Capability Assessment

The detailed comparison of MLOps capabilities between Weka and KNIME is summarized in Table 1, which evaluates both platforms across multiple dimensions critical for modern machine learning operations.

Table 1: Detailed MLOps Capability Comparison

MLOps Dimensions	Sub-criteria	Weka	KNIME	Rationale
Workflow Reproducibility	Version control	2/5	5/5	Weka: Manual backup; Knime: Git integration
	Documentation	3/5	5/5	Weka: Limited metadata; Knime: Self – documenting Workflows
	Enviroment	1/5	4/5	Weka: JVM – dependent; KNIME: Container support
Pipeline Automation	Scheduling	2/5	5/5	Weka: Basic; Knime: Enterprise scheduler
	Error Handling	2/5	4/5	Weka: Limited; Knime: Comprehensive node error handling
	Conditional Excution	1/5	4/5	Weka: not supported; Knime: Flow variable control
Deployment Readiness	Model serving	2/5	5/5	Weka: Custom code; Knime: RestApi generation
	Monitoring	1/5	4/5	Weka: Manual; Knime: Integrated performance tracking
	Scalability	2/5	5/5	Weka: Single – node; Knime: Distributed execution
Integration & Extensibility	Data Sources	3/5	5/5	Weka: Basic file/ DB; Knime: 100+ connectors
	Custom code	4/5	5/5	Both support Java/Python/R integration
	Community Ecosystem	4/5	5/5	Weka: Academic focus: Knime: Enterprise focus

The comparative results presented in Fig. 5 further illustrate the performance differences between Weka and KNIME across various analytical tasks.

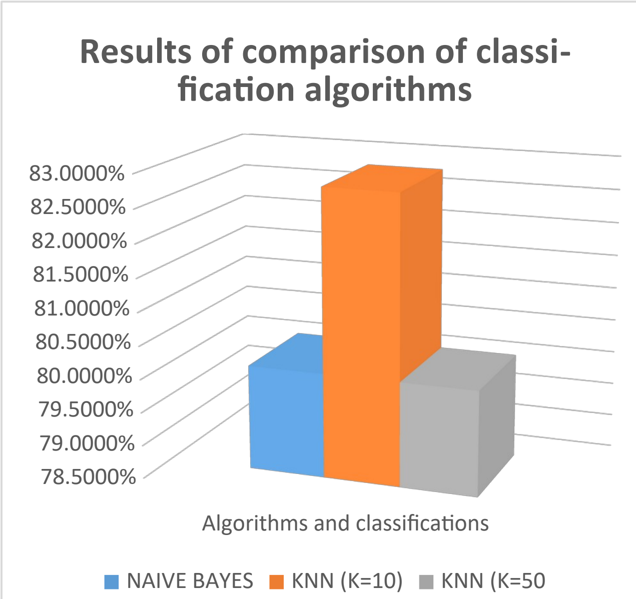

Fig. 5. *Comparative results*

Performance and Usability Analysis

Beyond MLOps capabilities, we observed significant differences in practical implementation:

Development Velocity:

- Weka: Rapid initial model development (2-3 hours for basic workflows);
- KNIME: Longer setup time (4-6 hours) but faster iteration once established.

Maintenance Overhead:

- Weka: High maintenance for production deployment requiring custom integration;
- KNIME: Lower operational overhead with built-in deployment tools.

Learning Curve:

- Weka: Accessible for statisticians and researchers;
- KNIME: Requires understanding of data engineering concepts but provides greater long-term value.

Implications for Educational Institutions

The findings have significant implications for educational data mining initiatives. While Weka offers immediate analytical capabilities, KNIME provides sustainable infrastructure for ongoing data-driven decision making. This aligns with research showing that "MLOps enables continuous delivery of high-performing models in production" [10].

For institutions with limited Information Technology (IT) resources, the hybrid approach we propose - using Weka for exploratory analysis and KNIME for operationalization - balances immediate needs with long-term sustainability. This strategy addresses the "deployment gap" commonly observed in educational analytics projects [12].

IV. CONCLUSION

This study demonstrates that while Weka remains valuable for algorithmic prototyping in Educational Data Mining (EDM), KNIME's architecture better supports MLOps principles. Its visual pipeline creation promotes reproducibility, while KNIME Server facilitates operationalisation. For educational institutions, we recommend a hybrid approach: using Weka for initial model exploration and KNIME for production deployment.

Future work will implement this approach in a student performance prediction system, measuring improvements in deployment efficiency and model reliability. Further research could explore how "no-code AI platforms can leverage MLOps" [62] in educational contexts.

Acknowledgments: This study was partially supported by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia, and these results are parts of Grant No ***451-03-136/2025-03/ 200066*** *and* ***451-03-136/2025-03/200132*** *with the University of Kragujevac - Faculty of Technical Sciences Čačak.*

REFERENCE

[1] "A Big Data smart library recommender system for an educational institution." ResearchGate, 2018.
[2] "MLOps for evolvable AI intensive software systems." ResearchGate, 2022.
[3] "MLOps: A Taxonomy and a Methodology." IEEE Access, 2022.
[4] "Machine Learning Operations: A Survey on MLOps Tool Support." arXiv, 2022.
[5] "MLOps: Practices, Maturity Models, Roles, Tools, and Challenges – A Systematic Literature Review." 2022.
[6] Abdullah, Qasem, Mohammed, & Emad. "A Comparison Study between Data Mining Tools over some Classification Methods." International Journal of Advanced Computer Science and Applications, 2011.
[7] Jović, A., Brkić, K., & Bogunović, N. "An overview of free software tools for general data mining." MIPRO 2014, 2014.
[8] "An Analysis of MLOps Practices." ResearchGate, 2023.
[9] "Machine Learning Operations (MLOps): Overview, Definition, and Architecture." ResearchGate, 2023.
[10] "The Pipeline for the Continuous Development of Artificial Intelligence Models." ResearchGate, 2023.
[11] "MLOps Spanning Whole Machine Learning Life Cycle: A Survey." ResearchGate, 2023.
[12] "From DevOps to MLOps: Overview and Application to Electricity Market Forecasting." ResearchGate, 2022.
[13] "Teaching Tip: Using No-Code AI to Teach Machine Learning in Higher Education." ResearchGate, 2024.