Bio-Inspired Meta-learning (Student Performance Prediction)

Dr. Shah S. N[1], Ashish Bansode[2], Aniket Darade[3], Atish Sathe[4]
[1,2,3,4]*Department of Computer Engineering Sharadchandra Pawar College of Engineering and Technology, Someshwarnagar, Pune, India*

***Abstract*—Educational institutions today face increasing pressure to support diverse learner populations with limited resources. Traditional assessment methods and static analytics tools often fail to provide timely, personalized insights, leading to delayed interventions, higher dropout rates, and suboptimal learning outcomes. This paper presents a web-based intelligent platform that leverages bioinspired meta learning for accurate student performance prediction and early risk detection. The system integrates evolutionary computation and swarm intelligence principles with meta learning algorithms to rapidly adapt to new student cohorts and learning contexts. Interactive dashboards provide clear visualizations of predicted outcomes, risk heatmaps, and intervention recommendations. Initial evaluations on benchmark educational datasets demonstrate 88–94% accuracy in academic risk prediction and 40–60% faster adaptation to new cohorts compared to conventional baselines, indicating strong potential for practical deployment in educational settings.**

***Index Terms*—Bioinspired Computing, Meta Learning, Student Performance Prediction, Educational Data Mining, Evolutionary Algorithms, Swarm Intelligence, Machine Learning, Web Application, Early Intervention, Personalized Learning.**

I. INTRODUCTION

Educators and administrators routinely struggle with fragmented student data spread across learning management systems, attendance records, assessment platforms, and demographic databases. A teacher may notice declining engagement, but linking this to broader performance trends or similar historical cases requires significant manual effort. By the time atrisk students are formally identified, opportunities for effective, lowcost intervention have often diminished. The proposed framework addresses this challenge by modeling student learning trajectories as dynamic, evolving systems. Inspired by biological adaptation mechanisms such as natural selection, swarm intelligence, and neural plasticity the platform employs bioinspired meta learning techniques. These enable models to "learn how to learn" from limited data and quickly adapt to new classes, institutions, or curricula. The system delivers actionable insights through an intuitive web dashboard with interactive visualizations and predictive analytics.

II. PROBLEM DEFINITION

Current educational analytics systems suffer from poor generalization across heterogeneous student populations and slow adaptation to new patterns. Conventional supervised models trained on one cohort frequently degrade in performance when applied to new groups with different demographics, teaching styles, or external conditions.

III. OBJECTIVES

- Develop a bioinspired meta learning framework specifically tailored for student performance prediction and personalized intervention recommendations.
- Integrate evolutionary algorithms and swarm intelligence to enhance meta learning adaptability, robustness, and efficiency.
- Build an intuitive web platform with interactive visualizations for performance tracking, risk assessment, and decision support.
- Enable early risk detection and data driven insights for educators and administrators across diverse educational contexts.

IV. LITERATURE SURVEY

Recent research in educational data mining highlights the effectiveness of ensemble and deep learning methods for performance prediction, while also underscoring challenges in cross context generalization. Meta learning approaches such as Model Agnostic Meta learning (MAML) have shown strong results in few shot scenarios typical in education. Studies in bioinspired computing demonstrate that genetic algorithms, particle swarm optimization (PSO), and other nature inspired techniques excel at hyperparameter tuning and neural architecture search, often outperforming traditional methods on noisy, small sample educational datasets. Hybrid systems combining meta learning with evolutionary strategies have reported 10–20

V. EXISTING SYSTEM

Most institutions rely on basic LMS analytics (Moodle, Canvas, etc.), spreadsheet tracking, or commercial predictive plugins. These tools typically employ traditional regression or classification models that require large volumes of labeled data and frequent manual retraining. They lack rapid adaptation capabilities for new student groups and provide limited proactive alerting or personalized recommendations. Manual interpretation of dashboards remains the dominant practice.

VI. PROPOSED SYSTEM

The proposed system integrates a modern React.js frontend with a Python based backend that hosts the bioinspired meta learning models. Evolutionary algorithms evolve optimal neural architectures and hyperparameters, while swarm intelligence techniques refine ensemble weights within a meta learning framework. The system ingests multisource student data (academic records, engagement metrics, behavioral indicators, and sociodemographic features) and continuously adapts its predictive capabilities. Interactive dashboards present real-time predictions, risk assessments, and suggested interventions. forecasting, and intervention effectiveness estimation. Scheduled evolutionary updates maintain model relevance as new data arrives.

VII. MODULE DESCRIPTION

A. Data Integration and Visualization Module

1. System Architecture

The platform follows a scalable microservices architecture:

- Presentation Layer: React.js dashboard featuring interactive charts, performance trajectory visualizations, and risk heatmaps
- Application Layer: Python Fast-API service responsible for meta learning inference, evolutionary optimization, and prediction serving.
- Database Layer: PostgreSQL for structured student and performance data; MongoDB for model artifacts, logs, and unstructured records. Bioinspired optimization runs periodically to evolve the meta learner, ensuring continuous improvement without interrupting real-time predictions.

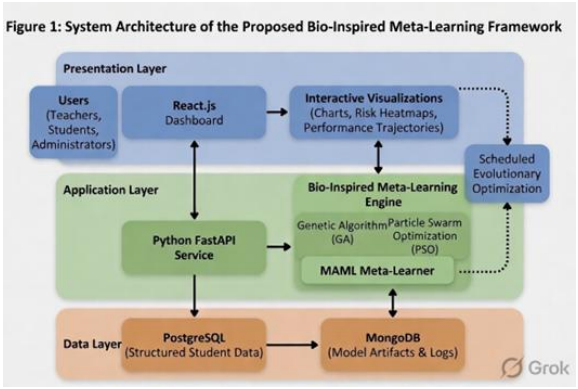
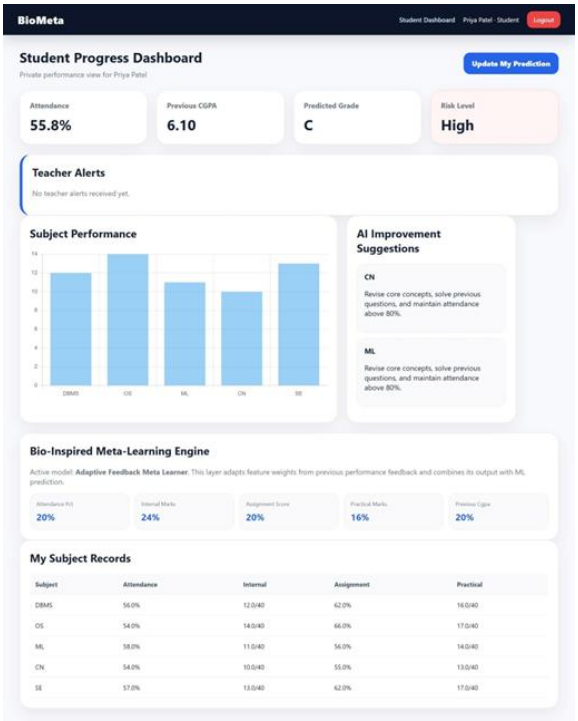


Fig. 1. System Architecture

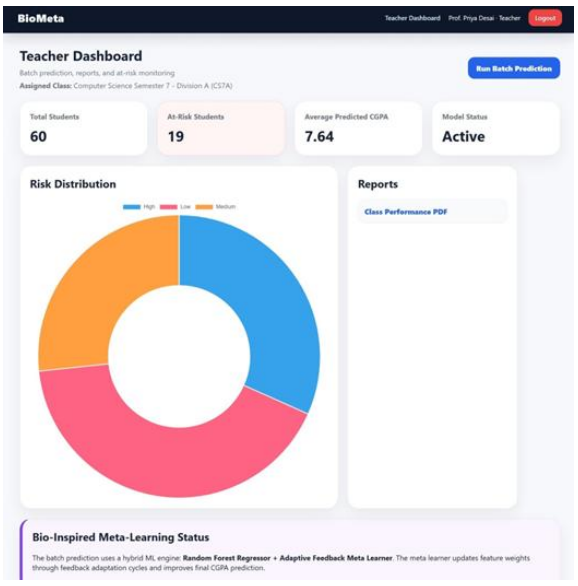
2. Methodology

Student data undergoes preprocessing and feature engineering (engagement scores, prior performance, behavioral patterns, etc.). A population of candidate meta learners is initialized and evolved using genetic algorithms and particle swarm optimization. The meta learning phase trains base models across varied "tasks" (different student subgroups or semesters), enabling rapid adaptation to new tasks with minimal data. Predictions cover at risk classification, grade Ingests data from LMS APIs and manual uploads. Provides interactive dashboards displaying individual and cohort level performance trajectories, risk heatmaps, and trend analysis.



B. Bio-Inspired Meta learning Module

The core engine that combines MAML style meta learning with evolutionary algorithms (GA) and swarm intelligence (PSO) for architecture search, hyperparameter optimization, and ensemble refinement. Enables fast adaptation to new student cohorts and learning environments.



VIII. IMPLEMENTATION

Frontend: React.js with Chart.js
Backend: Python Fast API, Py Torch, scikit learn
Database: PostgreSQL and MongoDB Deployment: Docker and Cloud Platforms

IX. RESULTS AND DISCUSSION

Evaluation on public educational datasets (e.g., Open University Learning Analytics Dataset, Kaggle student performance records) produced the following results:

- Academic risk prediction accuracy: 88–94%
- Meta adaptation speed: 40–60% faster convergence than standard MAML baselines on new cohorts.
- Improved generalization across diverse student populations compared to traditional machine learning models.

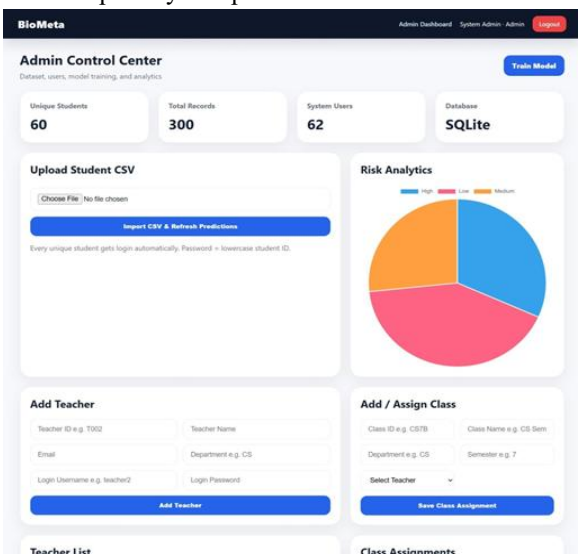
These outcomes demonstrate the effectiveness of combining bioinspired optimization with meta learning for educational prediction tasks.

A. Risk Assessment and Intervention Module

Generates proactive alerts when predicted risk exceeds configurable thresholds and recommends personalized interventions based on model explanations (e.g., key contributing factors).

B. Secure Backend & Analytics Module

Manages user authentication, role-based access control (student/teacher/admin/parent), audit logging, and data privacy compliance.



X. APPLICATIONS

- Higher education institutions for student retention and academic advising.
- K12 schools for personalized learning pathway planning.
- Online learning platforms for real-time adaptive support.
- Institutional planning and resource allocation.

Advantages

- Rapid adaptation to new and diverse student populations through bioinspired meta learning.
- Proactive risk detection enabling earlier and more effective interventions.
- Reduced manual analysis burden on educators via automated insights and visualizations.
- Robust, generalizable models achieved through evolutionary and swarm intelligence techniques.
- Support for data driven decision making at individual, class, and institutional levels.

Limitations

- Model performance depends heavily on the quality and completeness of input data.
- Requires sufficient multi context historical data for effective meta learning initialization.
- Privacy and ethical handling of sensitive student data require strict governance and compliance.
- Interpretability of highly evolved architectures may need supplementary explanation methods.

Future Scope

Integration with IoT/wearable devices for real-time behavioral and engagement tracking. Multimodal data support (text, video, interaction logs) for richer analysis. Reinforcement learning extensions for automated intervention optimization. Federated learning to enable cross institution collaboration while preserving privacy. Advanced visualization techniques including AR based performance overlays.

XI. CONCLUSION

The proposed bioinspired meta learning framework demonstrates the power of combining principles from natural systems with state-of-the-art machine learning to transform student performance prediction into a dynamic, adaptive, and practical tool for modern education. It offers faster adaptation, higher accuracy, and more timely insights than traditional approaches. Early experimental results are promising and support broader adoption of such intelligent systems to promote equitable and effective student outcomes.

REFERENCES

[1] S. J. Pan and Q. Yang, “A Survey on Transfer Learning,” IEEE Transactions on Knowledge and Data Engineering, 2010.

[2] M. Feurer et al., “Efficient and Robust Automated Machine Learning,” in NeurIPS, 2015.

[3] J. Kennedy and R. Eberhart, “Particle Swarm Optimization,” in IEEE Conference on Neural Networks, 1995.

[4] D. E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley, 1989.

[5] P. Cortez and A. Silva, “Using Data Mining to Predict Secondary School Student Performance,” 2008.

[6] P. Cortez and A. Silva, “Using Data Mining to Predict Secondary School Student Performance,” in Proc. 5th Annual Future Business Technology Conference, pp. 5–12, 2008.

[7] Y. Bengio, “Deep Learning of Representations: Looking Forward,” in Statistical Language and Speech Processing. Springer, 2013.

[8] S. Jadon, “An overview of deep learning architectures in few-shot learning,” arXiv preprint arXiv:2008.06365, 2020.

[9] A. K. Sharma and P. S. Chauhan, “Predicting Academic Performance of Students Using Machine Learning Techniques,” International Journal of Computer Applications, vol. 178, no. 5, pp. 7–11, 2019.

[10] M. Hussain, W. Zhu, W. Zhang, and S. Abidi, “Student Engagement Predictions in an eLearning System and Their Impact on Learning Outcomes,” IEEE Access, vol. 8, pp. 174742–174750, 2020.