



Journal of Interdisciplinary Science & Technology

Explainable Machine Learning Framework for Predicting the Academic Performance of Deaf and Hard-of-Hearing (DHH) Students

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DOI:10.5281/zenodo.23345848

Abstract: Deaf and Hard-of-Hearing (DHH) students face communication and language barriers that most academic-performance prediction systems overlook, since such systems are designed for hearing populations and ignore deafness-related factors such as communication mode, hearing-loss degree, family history of deafness, and age of speech-therapy intervention. This paper proposes an explainable machine learning framework, developed as a Computer Engineering academic project, to classify DHH students into High, Middle, and Low-performance categories using socio-economic, prior-academic, and deafness-related features. Since real-world DHH datasets are small and imbalanced, the pipeline uses synthetic data generation and SMOTE-based balancing before training classical and ensemble classifiers such as SVM, Random Forest, XGBoost, ExtraTrees, and a stacked ensemble. SHAP and LIME generate transparent, actionable explanations for teachers, parents, and policymakers. As the system is at the design stage, this paper reports the proposed architecture, methodology, and evaluation protocol rather than empirical results, contributing a reproducible template for explainable, imbalance-aware learning in an underserved educational domain.

Keywords: Deaf and Hard-of-Hearing education, explainable artificial intelligence, SHAP, LIME, SMOTE, ensemble learning, at-risk student prediction, inclusive EdTech

I. INTRODUCTION

Deaf and Hard-of-Hearing (DHH) students encounter obstacles in higher education that are qualitatively different from those faced by their hearing peers. Hearing loss of any type or degree can act as a barrier to learning, and an inaccessible classroom environment makes sustained academic progress difficult for many DHH scholars. In India alone, hundreds of government-funded schools serve DHH students at the school level, yet only a small number of institutes extend undergraduate opportunities to this population, which restricts both the availability of higher education and the data available for research.

Conventional academic-performance prediction systems are almost always designed with hearing students in mind. They typically rely on demographic, socio-economic, and prior-

academic variables while overlooking deafness-related factors communication mode (sign language, speech, or both), degree and type of hearing loss, family history of deafness, and the age at which speech therapy or early intervention began — all of which have been reported to strongly influence a DHH student's academic trajectory. A prediction model that ignores these factors is unlikely to generalize well to DHH learners.

Machine Learning (ML) offers a practical route to identify at-risk DHH students early enough for teachers and institutions to intervene. However, most ML systems deployed in education behave as 'black boxes': they output a classification without indicating why that classification was reached. This opacity limits the trust that teachers, parents, and policymakers place in automated recommendations, and it prevents the kind of targeted, factor-specific intervention that DHH students often need. Explainable Artificial Intelligence (XAI)

techniques in particular SHAP and LIME address this gap by attributing a model's prediction to specific input features, both globally across a dataset and locally for a single student.

This paper presents the design of an explainable ML framework that combines ensemble classifiers with SHAP- and LIME-based explanation layers to predict and explain DHH academic performance. The framework was developed as a final-year Computer Engineering group project (Project Synopsis, Group No. 31, Sandip Institute of Technology and Research Centre, Nashik) and is presented here in the structure of a conference paper, describing the proposed pipeline, feature schema, and evaluation protocol. The remainder of this paper is organized as follows. Section II reviews related work in DHH academic-performance prediction and explainable student-performance modelling. Section III states the problem addressed. Section IV describes the proposed system architecture. Section V details the methodology stage by stage. Section VI defines the proposed feature schema. Section VII outlines the evaluation protocol and situates it against literature-reported benchmarks. Section VIII lists implementation requirements, Section IX discusses the expected social relevance of the work, and Section X concludes with future scope.

II. RELATED WORK

Educational Data Mining (EDM) has been used broadly to classify students by academic performance, identify at-risk learners, and predict marks using demographic, behavioural, and academic variables. Ensemble methods such as Random Forest, XGBoost, and stacked classifiers are frequently reported to outperform single classical models on structured educational data because they combine complementary decision boundaries and reduce variance. Class-imbalance correction methods, most notably SMOTE, are commonly paired with these ensembles when the target classes such as High, Middle, and Low performers are unevenly represented, as is typical in small institutional datasets.

Research specifically addressing DHH academic performance is comparatively limited. One study examined the academic status and classroom progress of DHH students in general education settings and highlighted persistent gaps relative to hearing peers. Another study on the academic achievement of DHH students in an ASL/English bilingual program found that sign-language proficiency significantly affects outcomes. Further work modelled predictors of academic success among deaf college students using statistical methods on data that were not made openly available. Other research applied educational data-mining techniques to predict the performance of DHH students in Saudi Arabia, reporting that grades, demographics, geographic region, school, and course-related variables correlate strongly with outcomes. Additional work

reviewed the relationship between unilateral hearing loss and academic performance, questioning whether traditional assumptions about mild hearing loss still hold, and further research reported that even mild hearing loss in schoolchildren is associated with measurable school-performance differences.

Table 1: Summary of reviewed literature on DHH academic-performance prediction

Study	Focus / Population	Method / Approach	Key Finding
Study 1	DHH students, general education	Classroom progress tracking	Persistent gaps vs. hearing peers
Study 2	DHH students, ASL/English bilingual program	Academic achievement study	Sign-language proficiency significantly affects outcomes
Study 3	Deaf college students	Statistical modeling (data not public)	Predictors of academic success identified
Study 4	DHH students, Saudi Arabia	Educational data-mining techniques	Grades, demographics, region, school, course variables correlate with outcomes
Study 5	Unilateral hearing loss	Literature review	Challenges traditional mild-hearing-loss assumptions
Study 6	Schoolchildren, mild hearing loss	Empirical study	Measurable school-performance differences even with mild loss
Study 7	DHH students, India (454 records)	Stacked ensemble (XGBoost+RF+ExtraTrees) + SHAP/LIME, SMOTE	Communication mode, early intervention, schooling type, family history most influential

The most directly relevant prior work developed a stacked ensemble (XGBoost, Random Forest, and ExtraTrees) combined with SHAP and LIME to classify DHH students collected from higher-education institutes across India into three performance grades, using synthetic data generation and SMOTE to address a small, imbalanced dataset of 454 records. That study reported that communication mode, early intervention, schooling type, and family history of deafness were the most influential deafness-related predictors. The present project adopts a broadly similar ensemble-plus-XAI pipeline as its starting design, but is scoped as a fresh, independent implementation with its own data-collection and evaluation plan rather than a reproduction of that study; the proposed feature schema, evaluation protocol, and system architecture in Sections IV–VII are accordingly presented as

this project's own design choices, informed by but not copied from that earlier work.

On the explainability side, SHAP was introduced as a unified, game-theoretic approach to feature attribution, while LIME was introduced as a model-agnostic technique that fits a local, interpretable surrogate model around a single prediction. A systematic review of explainable student-performance prediction models found that XAI adoption in education remains comparatively rare relative to other domains such as credit risk or clinical diagnosis. Other work combined ensemble models with Shapley-based explanations to predict and interpret general student performance, and a broader framework (XAI-ED) was proposed for designing explainable educational AI tools. Separate research discussed the importance of bilingual language planning for deaf children, reinforcing why communication mode is a recurring predictive factor in this population.

Taken together, the literature indicates that (a) deafness-related factors materially affect DHH academic outcomes, (b) ensemble ML with imbalance correction performs well on small institutional datasets, and (c) XAI methods such as SHAP and LIME can make such predictions trustworthy for non-technical stakeholders. However, work that integrates all three elements specifically for DHH learners remains limited to a small number of studies. This motivates the present project.

III. PROBLEM STATEMENT

Academic-performance prediction models built for hearing students do not generalize well to Deaf and Hard-of-Hearing students because they fail to capture deafness-related factors such as communication mode, degree of hearing loss, and early-intervention history. In addition, most ML models deployed in education act as black boxes and provide no explanation for their predictions, which limits their trust and actionable use by teachers, parents, and policymakers. Finally, real-world DHH datasets are typically small and imbalanced across performance classes because only a limited number of institutes offer higher education to this population, which further reduces the reliability of naively trained ML models.

There is therefore a need for an explainable machine learning system, tailored specifically to DHH students, that can (a) reliably predict at-risk students despite a small and imbalanced dataset, and (b) clearly explain the deafness-related and academic factors driving each prediction, so that timely and targeted support can be provided by teachers, parents, and institutions.

IV. PROPOSED SYSTEM ARCHITECTURE

Figure 1 shows the proposed six-stage pipeline. The design follows the standard structure adopted in explainable-ML

pipelines for education: raw student data is collected, cleaned and encoded, rebalanced across performance classes, used to train and compare several classifiers, and finally passed through an explainability layer whose output is converted into recommendations for stakeholders.

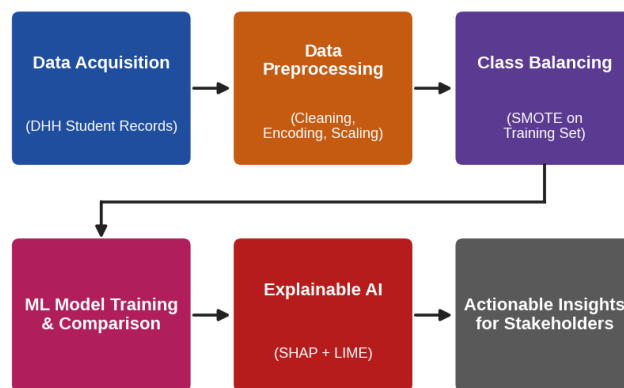


Figure 1: Proposed explainable ML pipeline for DHH student academic-performance prediction.

The pipeline in Figure 1 begins with data acquisition, in which socio-economic, prior-academic, and deafness-related attributes are gathered or synthetically generated following the feature schema described in Section VI, and proceeds through preprocessing, class balancing, model training and comparison, and explainability, before producing insights for stakeholders. Each stage is described below.

V. METHODOLOGY

A. Stage 1 – Data Acquisition

Student records covering socio-economic, prior-academic, and deafness-related features are to be collected through institutional records and a consent-based survey, or synthetically generated where direct access is limited, following the feature categories established in DHH education research. Given the small number of institutes offering higher education to DHH students, the dataset is expected to be modest in size, which motivates the class-balancing stage described below.

B. Stage 2 – Data Preprocessing

Missing values are handled by deletion of majority-empty records and mean/mode imputation for partially missing fields. Categorical features (e.g., gender, communication mode, type of schooling) are label-encoded, and numerical features are standardized so that no single feature dominates distance- or gradient-based learning:

$$X_i = (x - \mu) / \sigma$$

where x is the raw feature value, μ its mean, and σ its standard deviation across the training set. Semester-1 marks are

subsequently discretized into three ordinal grades A (High), B (Middle), and C (Low) which form the classification target.

C. Stage 3 – Class Balancing (SMOTE)

Because DHH performance classes are expected to be imbalanced (the Middle-performer class typically dominating, as reported in comparable studies), the Synthetic Minority Oversampling Technique (SMOTE) is applied to the training partition only. SMOTE synthesizes new minority-class instances by interpolating between a minority sample and one of its k nearest minority-class neighbours in feature space, which reduces the risk of the majority class dominating the learned decision boundary while avoiding leakage of synthetic instances into the held-out test set.

D. Stage 4 – Model Building and Comparison

A set of classical and ensemble classifiers is proposed for comparison: Logistic Regression and Naïve Bayes as linear/probabilistic baselines; Decision Tree and K-Nearest Neighbours as simple non-linear baselines; Support Vector Machine for high-dimensional margin-based classification; and Random Forest, XGBoost, and ExtraTrees as ensemble methods expected to capture non-linear feature interactions more effectively. A stacked ensemble combining XGBoost, Random Forest, and ExtraTrees as base learners is additionally proposed, following the combination strategy reported to be effective in comparable DHH-performance studies. Hyperparameters for each model are to be selected via grid-search cross-validation on the training partition only.

E. Stage 5 – Explainability (SHAP and LIME)

Once the best-performing classifier is identified using the metrics in Section VII, its predictions are to be explained using two complementary XAI techniques. SHAP assigns each feature f a Shapley value representing its average marginal contribution across all feature-subset coalitions:

$$\phi_i(f, x) = \sum [|z'|! (M - |z'| - 1)! / M!] [f_x(z') - f_x(z'^{-i})]$$

where M is the number of input features and the summation runs over all feature subsets z' that exclude feature i . SHAP summary and force plots are proposed to provide both global (dataset-level) and local (single-student) explanations. LIME complements this by fitting a locally faithful linear surrogate model g around a single prediction:

$$\zeta(x) = \operatorname{argmin}_g L(f, g, \Pi_x) + \Omega(g)$$

where L measures how well g approximates the complex model f in the neighbourhood Π_x of instance x , and $\Omega(g)$ regularizes the surrogate's complexity. Applying both methods allows cross-validation of feature-importance claims: a factor identified as influential by SHAP's global ranking can be checked against LIME's local explanations for individual at-risk students, which is intended to increase the

trustworthiness of the reported factors for non-technical stakeholders.

F. Stage 6 – Evaluation and Reporting

The best-performing model is to be validated using a confusion matrix, class-wise sensitivity and specificity, ROC-AUC, and stratified k -fold cross-validation to assess generalization. Explanation quality is proposed to be checked in two ways: (i) comparing the model's global feature-importance ranking against rankings independently supplied by education-domain experts using a Spearman rank-correlation coefficient, and (ii) computing a cosine-similarity score between LIME's local explanation weights and the model's permutation feature importance across a random sample of instances, following the validation approach reported in comparable work.

VI. PROPOSED FEATURE SCHEMA

Table 2 summarizes the proposed feature schema, organized into the same three categories used in comparable DHH-performance research: socio-economic features, prior-academic features, and deafness-related features. This project's schema adds explicit encoding for hearing-aid and cochlear-implant usage as a standalone feature (rather than folding it into hearing-loss degree), so that SHAP/LIME explanations can separately attribute the effect of assistive-device usage from the effect of hearing-loss severity a distinction the group intends as this project's own refinement of the feature design.

Table 2: Proposed feature schema for DHH performance prediction

Category	Proposed Feature	Values / Type
Socio-economic	Gender	Male, Female
Socio-economic	Family income	Categorical (income brackets)
Socio-economic	Parents' education	No formal – PhD (ordinal)
Prior-academic	Type of schooling (Class 10/12)	Special School, Regular School
Prior-academic	Percentage marks (Class 10/12)	Numeric: 0–100
Prior-academic	Semester-1 marks (target basis)	Numeric → discretized A/B/C
Deafness-related	Communication mode	Sign, Speech, Both
Deafness-related	Type / degree of hearing loss	Mild – Profound (ordinal)
Deafness-related	Speech therapy (below / above age 5)	Yes, no
Deafness-related	Hearing-aid / cochlear-implant use	Yes, no
Deafness-related	Family history of deafness	Yes, no

VII. EVALUATION PROTOCOL AND LITERATURE BENCHMARKS

As this framework is at the design and implementation-planning stage, no experimental results are reported in this paper. The intended evaluation protocol is: (i) a stratified train-test split with SMOTE applied to the training partition only; (ii) comparison of all classifiers listed in Section V-D using Accuracy, Precision, Recall, and F1-Score; (iii) selection of the best model followed by k-fold cross-validation to estimate generalization; and (iv) SHAP/LIME-based explanation validation against domain-expert rankings, as described in Section V-F.

Table 3 lists literature-reported benchmarks for comparable DHH and general student-performance prediction studies. These figures are reproduced from the cited sources for context only; they are not results of the present project and should not be read as such. They are included so that, once the proposed pipeline is implemented and evaluated, its own results can be meaningfully situated against prior work.

Table 3: Literature-reported benchmarks (for context only not results of this project)

Study	Model	Reported Accuracy	Domain
Study 1	Stacked (XGBoost+RF+ExtraTrees)	92.99% (ROC-AUC 0.978)	DHH performance (India)
Study 2	Ensemble + SHAP	Reported in original study	General student performance
Study 3	EDM / regression-based	Reported in original study	DHH performance (Saudi Arabia)

VIII. IMPLEMENTATION REQUIREMENTS

A. Hardware Requirements

- Processor: Intel Core i3/i5 or AMD Ryzen 3/5 or higher
- RAM: Minimum 8 GB (16 GB recommended)
- Storage: 256 GB SSD or above
- Internet connectivity for library and dataset access

B. Software Requirements

- Operating System: Windows 10/11 (64-bit)
- Language: Python 3.10+
- IDE: Jupyter Notebook / Visual Studio Code
- Libraries: pandas, numpy, scikit-learn, XGBoost, imbalanced-learn (SMOTE), SHAP, LIME, matplotlib
- Optional deployment: Streamlit-based interactive prediction dashboard
- Version control: Git and GitHub

IX. SOCIAL RELEVANCE AND ALIGNMENT WITH SUSTAINABLE DEVELOPMENT GOALS

The proposed system is aligned with three United Nations Sustainable Development Goals. Under SDG 4 (Quality Education), the system is intended to enable early, data-driven identification of at-risk DHH students so that timely, individualized academic support can be provided, improving access to inclusive education. Under SDG 10 (Reduced Inequalities), by explaining why a DHH student is at risk for example, communication mode or lack of early intervention the system is intended to help teachers and policymakers narrow the educational gap between DHH students and their hearing peers. Under SDG 9 (Industry, Innovation and Infrastructure), the project is intended to demonstrate how machine learning and explainable AI can be responsibly applied to build transparent, trustworthy educational-technology infrastructure for an underserved learner population.

X. CONCLUSION AND FUTURE SCOPE

This paper has proposed an explainable machine learning framework for predicting the academic performance of Deaf and Hard-of-Hearing students, combining SMOTE-based class balancing, a comparison of classical and ensemble classifiers, and SHAP/LIME-based explainability. Unlike prediction systems designed for hearing students, the proposed feature schema explicitly incorporates deafness-related factors communication mode, degree of hearing loss, early-intervention history, and family history of deafness which prior work has shown to materially affect DHH academic outcomes. As the project is currently at the design stage, this paper has intentionally reported the proposed architecture, methodology, and evaluation protocol rather than experimental results.

Future work will focus on completing data acquisition, implementing and training the proposed classifiers, and reporting the resulting accuracy, precision, recall, F1-score, and SHAP/LIME-based explanations as an extension of this paper. Longer-term scope includes deploying an interactive Streamlit-based dashboard for teachers and policymakers, extending the framework toward multi-institution data collection, and evaluating the faithfulness of the generated explanations against feedback from special-education domain experts, following the validation approach used in comparable studies.

ACKNOWLEDGMENT

The authors thank Dr. Vijay Karwande, Project Guide, and Mr. Anmol Budhewar, Project Coordinator, Department of Computer Engineering, Sandip Institute of Technology and Research Centre, Nashik, for their guidance in defining the scope and methodology of this project.

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