Risk Prediction Through Deep Learning Classifiers for a Child Health Protection Decision Support System

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Abstract—This research presents the development and implementation of a Machine Learning Decision Support System (ML-DSS) aimed at enhancing child health protection in Zambia. The system utilizes a predictive framework based on a star-schema database architecture, which includes a fact table containing child-level data linked to various health and educational indicators. Specifically, the ML-DSS focuses on binary classification tasks to assess school dropout risks and stunting risks among children, employing deep learning techniques facilitated by TensorFlow. Key results highlight the model's performance metrics, demonstrating its potential to inform early interventions in child health and education. The research identifies critical factors influencing dropout rates and stunting, emphasizing the significance of nutrition and school attendance. Despite limitations, including the absence of detailed household financial data, the model provides a robust tool for NGOs to enhance their programming and improve child health outcomes.

Keywords—Machine Learning Decision Support System (ML-DSS), Child health protection, Star-schema database, Predictive framework, Binary classification, School dropout risk, Stunting risk, TensorFlow Deep Learning, Fact & Dimension Tables, Early intervention, NGOs programming, Data limitations, Zambia context, Feature engineering, Model evaluation

I. INTRODUCTION

How Machine Learning Decision Support Systems in Child Health work is that they use some algorithms in order to analyze datasets like health records, environmental data, etc. They use them in real time, to be able to predict risks pertaining to growth challenges and disease outbreaks. Such systems can recommend preventative actions or measures like flagging children at-risk for early interventions.

Traditional M&E Systems operate much slower due to manual and structured processes to monitor health metrics and evaluate programs' or projects' effectiveness like periodic surveys, checklists and reviews led by humans. In this way, the traditional monitoring and evaluation systems require much more time, are prone to human error, and are not flexible for adaptation to rapid changes or developments; of which this usually has the potential to delay intervention response to health threats.

Traditional M&E Systems operate much slower due to manual processes. They rely on human professionals and expertise, and although they can be consistent, they're less dynamic. In terms of initial cost investment, they cost less but are likely to require some ongoing labor resources. The strength of traditional M&E Systems lies in stable and consistent environments, but they're unfortunately less flexible to new data or unexpected dimensions. Although these systems have less risks to technical biases, they fall vulnerable to subjective errors and inconsistencies. They usually operate on standalone basis, and can be improved with some digital upgrades.

Machine Learning Decision Support Systems are about rapid analysis and real-time predictions, while presenting high accuracy with good quality data. They're able to improve even further with more learning. Initial Investment Cost for these systems is much higher but gradually becomes lower in the long term (operationally). Machine Learning Decision Support Systems are very good at handling data on a large-scale and around transformational or evolving trends (dynamics). They can be more prone to algorithmic biases or breaches of privacy, but these can be mitigated by regulations and standards, similar to GDPR. In terms of integration-ability or characteristics, they're able to complement different tools to achieve holistic health strategies.

While Traditional M&E Systems would mostly be used for evaluations that are routine work, e.g. growth monitoring and program assessments, Machine Learning Decision Support Systems would be used for diagnostics, early intervention and risk prediction. The prior gives priority to accessibility and decisions which are context specific, while the latter emphasizes the need for mitigation of bias and data privacy for the protection of vulnerable populations. Machine Learning Decision Support Systems achieve data privacy by infusing anonymity of data.

I. RELATED WORKS

A. *Involvementof Machine Learning Tools in Healthcare Decision Making*

The review's conclusion was that Machine Learning is inevitable in and vital for healthcare, with continuous advancements in precision medicine and Artificial Intelligence integration. Continuous growth of the phenomena was further expected in pandemics and resource management.

The authors ascertained that healthcare had been transformed by machine learning by infusion of computational decision making in difficult industries and sectors. It's very evident from this literature review that machine learning had become an integral component of biomedicine, driving and proving the possibility of accurate and cost-effective decision making.

B. *Machine Learning-based clinical decision support systems for pregnancy care: A systematic review*

Du et al., 2023 conducted a systematic review focusing on using machine learning in Clinical Decision Support Systems for prenatal care. The potential of CDSS to enhance healthcare delivery was highlighted, and this would be achieved through error reduction, improving diagnostics, and decision support throughout pregnancy.

The review was aimed at the identification of work in this field and to magnify some areas that would need further research: with its rationale being that machine learning CDSSs were appreciated and valued for optimizing the outcome of pregnancies, and yet bias, transparency and real-world practicability were yet to be explored much more.

C. *Review of Medical Decision Support and Machine-Learning Methods*

The article reflected early developments of Computer Decision Support in Medicine dating far back as the 1950s and evolving through systems like INTERNIST and MYCIN around the 1970s. In its evolution, it had been explored through Veterinary Medicine and Human Medicine. While the authors did touch on three types of machine learning categories (supervised; unsupervised; and reinforcement learning), they looked into the three detailed kinds of supervised learning, being Naïve Bayes, Decision Trees and Neural Networks. The subject three algorithms were marked off to be power tools for predicting diseases and were selected based on the types of data & problem complexity.

Emphasis was given on the importance of the quality of training data, and that features should be selected and transformed in order to gain good performance of the system. It was established that cross-validation ensures model reliability through testing of data subsets. Accuracy, sensitivity and specificity were used for performance metrics evaluation, and an example result was that Naïve Bayes scored about 88.4% accuracy on prediction of coronary heart disease.

D. *KIDMATCH to distinguish between MIS-C, Kawasaki disease and other febrile ilnesses in children*

Lam et al., 2022 explored development of a machine learning model built to differentiate three diseases (MIS-C; Kawasaki; and other febrile illnesses) through the usage of some clinical signs and laboratory data gathered from testing. The model architecture comprised of neural networks phased in two stages, where TensorFlow and logistic regression were used for baseline training.

From one thousand five hundred and seventeen patients (1517; diagnosed with either of the three illnesses) and split into a ratio of 80:20 for training and validation, a median AUC of 98.8% and 96.0% respectively, got achieved during the internal validation process. For detection of MIS-C the neural network demonstrated high sensitivity and specification, of 100%.

The prediction confidence was enhanced by incorporation of a conformal prediction framework so that in the process, and to work well, test samples could be rejected out of the distribution of the training set. The authors validated KIDMATCH using some external cohorts, which resulted in consistent performance among a number of hospitals with a confidence in predictions of MIS-C.

E. Machine Learning clinical decision support systems for surveillance: a study on pertussis and RSV in children

De Laco et al., 2023, carried out a case study of Pertussis and RSV infection in children, with contributing factors being that traditional clinical case definitions for pertussis had low specificity and not much utilities for care; there was no RSV surveillance, syndromic surveillance that could be scaled for RSV and pertussis; and Machine-Learning Clinical Decision Support Systems (ML-CDSS) for infectious diseases were emerging at the same time, but that unfortunately a very few of them targeted emergency or primary care type of settings.

For the study design and methods, the authors used infants under the age of one, who presented respiratory symptoms at an Italian pediatric ED between August 2015 and June 2020. They had collected the syndromic features of cough, stridor, hypoxia and emesis by means of a structured questionnaire. They also collected routine labs and multiplex PCR confirmation for B.pertussis and RSV, after which they developed four (4) models. The models they developed were: Pertussis Model 1A: syndromic + lab data; Pertussis Model 1B: syndromic data only; RSV Model 2A: syndromic + lab data; RSV Model 2B: syndromic data only.

In terms of performance, they found that Model 1A would miss about fourteen (14) pertussis cases and misdiagnose about fourteen (14). Model 2A would miss about six (6) RSV cases and misdiagnose about thirty-one (31).

TABLE 1 SUMMARY PRESENTATION OF RELATED WORKS

THEME	**KEY WORKS**	**STRENGTHS**	**LIMITATIONS**
Application of Machine-Learning approaches and algorithms to healthcare decision-making	Deo (2015); Obermeyer & Emanuel (2016); Debnath et al. (2020); Sanchez M et al. (2019); Cao et al. (2018; Jin & Dong (2016); Li et al. (2017); Carte & He (2016)	❖ Comprehensive breadth ❖ Historical context ❖ Comparative Insights ❖ Highlights ethical considerations	➢ Lacking quantitative meta-analysis ➢ Shallow algorithmic discussion ➢ Limited discussion on generalizability and external validation ➢ Sparse on real-world deployment challenges
Existing literature on machine-learning clinical decision support systems for pregnancy care – gestation stages	Antoniadi et al. (2021); Du et al. (2022); Van Calster et al. (2019); Gorthi et al. (2020); Jimenez-Serrano et al. (2021)	❖ Comprehensive scope ❖ Diversity of ML methods ❖ Emerging XAI ❖ Practical Prototypes	➢ Explainability gap ➢ Data/population bias ➢ Implementation shortfall ➢ Methodological blind spots ➢ Narrow generalizability
Systematic survey of Machine-Learning methods and architectures in medical decision support systems	▪ Stemming in free-text analysis ▪ Taxonomy-concept abstraction for evidence-based guidelines and syndromic surveillance ▪ Stop-word removals impact on feature-set reduction ▪ Filter vs. Wrapper approaches for optimizing feature subsets	❖ Breadth of coverage ❖ Empirically grounded ❖ Real World anchoring via the John Hopkins **MediAI** example ❖ Clear exposition of classic ML techniques	➢ Predominantly 'classical' ML ➢ Sparse treatment of explainable AI ➢ No unified benchmarking ➢ Limited discussion of deployment challenges
KIDMATCH to distinguish between MIS-C, Kawasaki disease and other febrile illnesses in children	Lam et al. (2022); Godfred-Cato et al. (2020); McCrindle et al. (2017); Nemati et al. (2021); Abrams et al. (2022)	❖ Two-stage prioritizing MIS-C identification, then KD vs. other febrile illnesses ❖ Conformed prediction framework enhances safety by rejecting uncertain or shifted-distribution cases ❖ Uses only features available at first evaluation, no specialized tests, facilitating broad deployability ❖ Interpretable via SHAP	➢ Retrospective design with potential-misdiagnosis in training/test labels ➢ Training KD and other febrile cohorts from a single center ➢ Thresholds may require site-specific calibration due to prevalence shifts ➢ Indeterminate cases lacking clinical workflow guidance beyond ordering further tests
Case-Study-driven development and evaluation of four machine-learning clinical decision support models for diagnosing pertussis and RSV infection in infants	Tozzi AE et al. (2020); McCord KA et al. (2023); Henning KJ (2004); Hughes HE et al. (2020); Nemati S et al. (2021); Lundberg SM & Lee S (2017); Baruchi J et al. (2022); Saadatian-Elahi M et al. (2016)	❖ Dual models broaden applicability ❖ Solid performance ❖ Interpretability ❖ Low missing-data rate and prospective data collection by research nurses	➢ Moderate predictive performance ➢ Class imbalance favors negative-case predictions ➢ Retrospective design ➢ No discussion of CDSS integration workflow

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			minimize bias ❖ Prototype easily integratable into EHRs or mobile apps for real-time clinical decision support and syndromic surveillance	

Figure 1: Comparison of Related Works

II. METHODOLOGY

This study adopts a supervised machine learning approach using deep learning (specifically feedforward neural networks) for classification. Deep learning got to be the choice because of its capacity to model complex, non-linear relationships across multiple variables, which is well-suited for health and education related prediction problems.

Traditional logistic regression and the decision tree approaches were considered but turned down due to:

- Limited performance on high-dimensional and non-linear data.
- Less flexibility when it comes to capturing interaction effects between school and health variables.

TensorFlow was selected for development of the model due to its scalability, GPU support, and community support.

The methodological approach used incorporates a close cohesion and synergy of the theoretical framework, system design, and research objectives, enabling a robust ML-DSS for enhanced child-health protection in Zambia.

A. Research Data and Datasets

The main and primary dataset consists of child records collected by NGOs across the different regions of Zambia. Each child record is linked to their respective school and health post.

Main Tables:
child (fact table) [4]: demographics, meals, attendance, vaccination, stunted status, dropout status.
school (dimension) [6]: school name, shift type, teacher-pupil ratio.
health_post (dimension) [5]: availability of services, distance.

Targeted Variables:
has_dropped_out (binary)
stunted (binary)
The data is synthetically augmented where necessary so real-world distributions are reasonably simulated while preserving privacy.

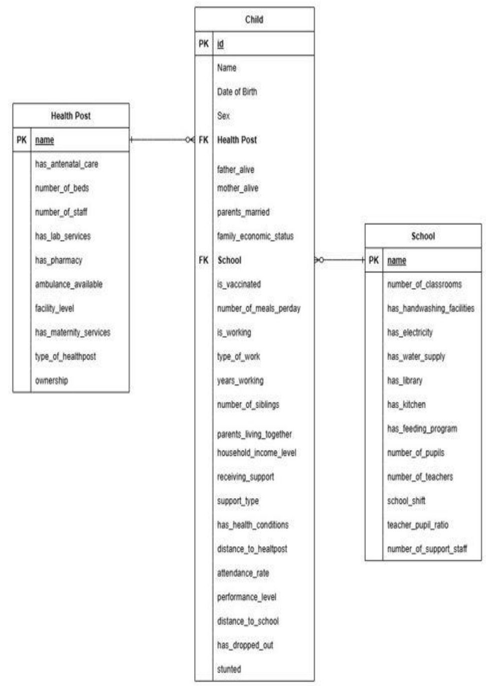

Figure 2: Star-Schema Entity Relationship Diagram of the Prototype

Data collection methods and data analysis techniques

Data collection:

A. Sourced from NGOs' existing child welfare tracking systems.
B. Supplemented with synthetic data based on known patterns from some UNICEF and WHO reports.

Data Analysis Techniques:
Data preprocessing: normalization, handling of missing values.
Feature selection using correlation analysis and domain knowledge.
Training/Validation split (80/20).

Model evaluation using precision, recall, F1-score, and confusion matrix.

Analysis also includes comparison with baseline models (e.g., logistic regression) to justify the deep learning approach.

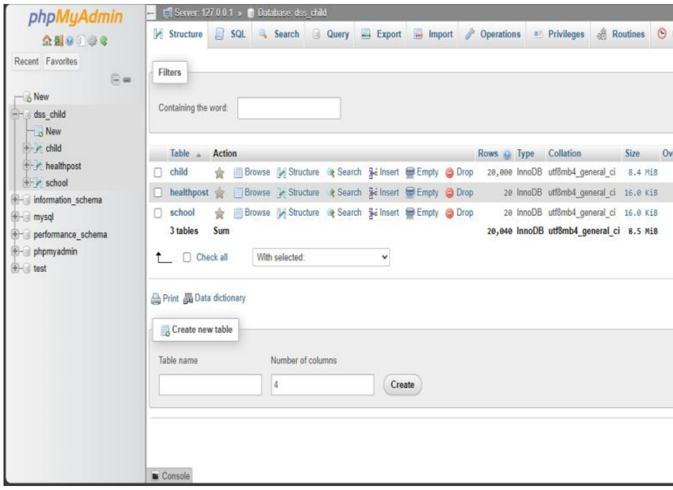

Figure 3: View of the Database Tables

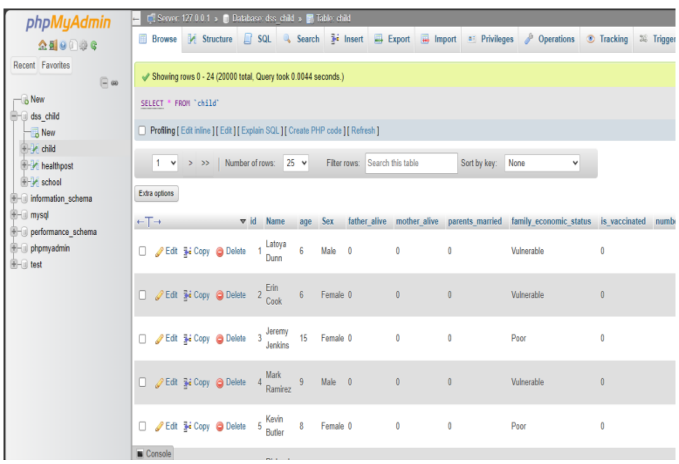

Figure 4: The Child Table

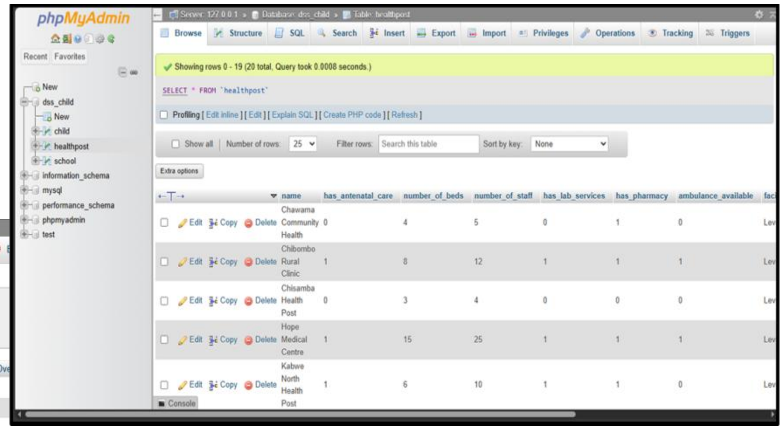

Figure 5: The Health Post Table

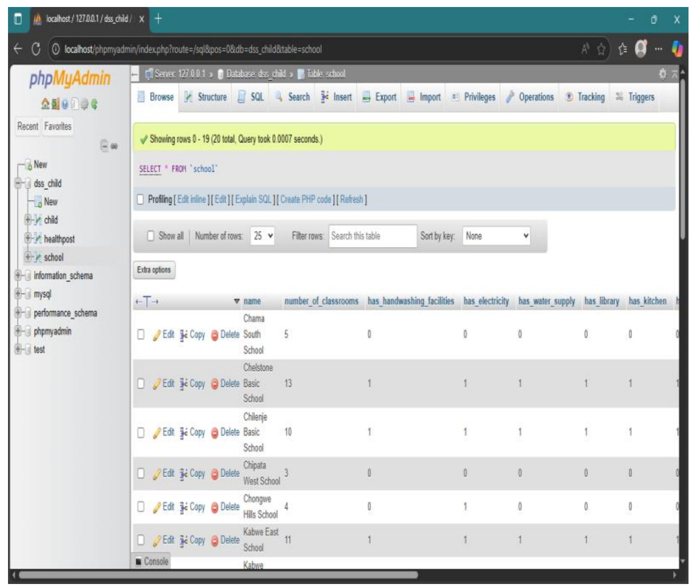

Figure 6: The School Table

III. PROTOTYPE, DATA, EXPERIMENTS, AND IMPLEMENTATION

The system implements a supervised machine learning approach using a feedforward neural network. The model architecture is based on a multi-layer perceptron (MLP), optimized using the Adam optimizer and trained with binary cross-entropy as the loss function. Categorical data was encoded using label encoding, and numeric features were standardized using StandardScaler to ensure uniform scale and convergence stability during training.

Data was split into training and test sets using an 80:20 ratio, ensuring both target classes are well represented.

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Although the current implementation uses static hyperparameters (e.g., fixed learning rate and batch size), the architecture allows for extension to grid search or other hyperparameter tuning mechanisms.

IV. DESIGNED PROTOTYPE, MODEL FRAMEWORK

The prototype comprises of two parallel ANNs:

Dropout Prediction ANN (annd)

Stunting Prediction ANN (anns)

Each model includes:

- **Input Layer**: Accepts 43 features derived from merged and preprocessed data.
- **Two Hidden Layers**: 43 and 21 units respectively, each using ReLU activation to allow the network to learn non-linear patterns.
- **Output Layer**: A single neuron with a sigmoid activation to yield probabilities for binary classification (0 = No, 1 = Yes).
- The structure is pyramid-shaped, with the first layer as the number of input features and the subsequent layers being the previous number divided by two.
- The models were implemented using TensorFlow's Sequential Application Programming Interface. After training for 100 epochs with a batch size of 1000, the models were serialized in .keras format for reuse. Feature scalers were saved separately for consistent preprocessing during deployment.

V. RESULTS AND DISCUSSIONS

The results presented in this section are derived from the training and testing of two Artificial Neural Networks (ANNs); one for predicting school-dropout and the other for predicting stunted growth. Both models were trained over 100 epochs, with training accuracy for the dropout model reaching **87%**, and **86%** for the stunting model.

On the test data, the performance was as follows:

Dropout ANN:

- **Test Accuracy:** 75%
- **Confusion Matrix:**
  - True Negatives (TN): 2021
  - False Positives (FP): 2073
  - False Negatives (FN): 1925
  - True Positives (TP): 9981

Stunting ANN:

Test Accuracy: 74%

Confusion Matrix:

True Negatives (TN): 6075

False Positives (FP): 1980

False Negatives (FN): 2040

True Positives (TP): 5905

The confusion matrices show that the models were effective in identifying a large number of positive cases (dropouts and stunted children), but that they also misclassified a notable number of instances.

A. ANALYSIS OF RESULTS/PERFORMANCE METRICS

While the training accuracy was quite high for both models (above 85%), the test accuracies of **75%** and **74%** suggest moderate generalization. This indicates that the models are learning relevant patterns from the training data.

Observations:

The **high number of false positives** in both models may lead to unnecessary interventions - which is not necessarily a bad thing.

The **false negatives**, although fewer, are more critical as they represent children at risk who are missed by the system.

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These results are typical in real-world classification tasks where imbalanced class distributions and overlapping feature spaces challenge model precision.

Although additional performance metrics such as **precision, recall, F1-score**, and **AUC-ROC** were not calculated in this iteration, they are important for future versions. Precision and recall especially would provide better insight into how well the model balances risk of over- an under- prediction.

B. COMPARISON TO RELATED WORKS

Most existing research in sub-Saharan Africa predicting dropout or malnutrition risk has relied on traditional machine learning models such as logistic regression, decision trees, or support vector machines. These models typically report test accuracies between **65% and 75%**, with limited ability to capture complex, nonlinear relationships among features.

For example, **Mutisya et al. (2019)** applied logistic regression to predict school dropout among vulnerable children in Kenya, achieving around 70% accuracy. Similarly, **Osei and Appiahene (2020)** used decision trees to analyze malnutrition predictors in Ghana, finding moderately accurate but highly interpretable models. However, these approaches struggled to capture multifactorial dependencies across health, education, and household characteristics.

This project's use of deep learning—specifically, fully connected ANNs—demonstrates a modest improvement over the baseline models, with accuracies near **75%** on test data and significantly higher training accuracies. The capability of ANNs to model higher-order feature interactions may account for this performance boost, as shown in recent health-focused deep learning applications in Africa (**Abdulrahman et al., 2021**; **Gichoya et al., 2022**).

C. IMPLICATIONS OF RESULTS

The performance of the models has several implications for deployment in real-world NGO programming in Zambia:

Early Warning System:
The models can be used as part of a digital decision support tool to flag high-risk children for further assessment by field staff or community workers.

Intervention Planning:
By identifying at-risk children using structured data, NGOs can better allocate limited resources—e.g., school feeding programs, psychosocial support, or community outreach.

Operational Limitations:
High false positives could result in unnecessary interventions, requiring a human-in-the-loop validation process. Conversely, false negatives suggest that models should be supplemented with other indicators or community feedback mechanisms.

Zambian Contextualization:
Factors such as **meals per day**, **school attendance**, **family income**, and **facility type** were strong predictors. These align with known determinants of educational attainment and child health in Zambia, supporting the validity of the model's outcomes.

VI. CONCLUSION

The study adopted a star-schema data warehouse integrating: Child demographics & nutrition; School attendance & performance; and Health-post records (vaccinations, growth), with a process of execution or implementation in this order, respectively: ETL → feature engineering → feed-forward neural network → binary risk predictions (dropout, stunting) → decision-support dashboard & alerts.

Qualitatively, it promotes and relies on a Theory of Change linking the infrastructure of the data, model outputs, stakeholder training to → targeted interventions → long-term impact (reduced stunting, improved retention).
The traditional models and mechanisms of machine learning (logistic regression, decision trees) exercised in similar African settings reported around 65–75% accuracy, while the deep-learning ANNs developed in this study demonstrated a modest but meaningful improvement, likely to be due to the capacity of ANNs to capture nonlinear and high-order feature interactions.

In future, it would be ideal to encorporate parental/household socioeconomic data and social-protection metrics, which the Parent dimensional Table would have likely achieved had it not been a challenge to gather reliable data for integration. The study also concluded on the need to explore some time-series models, similar to LSTM, for dynamic risk tracking. In terms of actual implementation of the model/framework, it would serve well deployed for evaluation in live NGO workflows centered on the same facets of developmental programming for continuous real-world feedback.

Explainability could also be enhanced (feature-importance, ROC/AUC curves) to maximize stakeholder trust and interpretability.

ACADEMIC CONTRIBUTION TO THE BODY OF KNOWLEDGE/NOVELTY

The contribution of this study to the body of knowledge is bridging traditional static M&E frameworks with dynamic, real-time data-driven decision support; by use of fully connected ANNs—demonstrating a modest improvement over the baseline models of logistic regression, decision trees, or support vector machines; with accuracies near **75%** on test data and significantly higher on training accuracies.

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