

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

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A Final Year Research Project submitted in partial fulfilment of the requirements for the degree of Master of Science in Information Technology

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

INTRODUCTION

1.1 Background to the study

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

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of bias and data privacy for the protection of vulnerable populations. Machine Learning Decision Support Systems achieve data privacy by infusing anonymity of data.

1.2 Problem Statement

Traditional M&E Systems, with or without application to the facet of Child Health & Social Protection, are bound to have late or delayed data before aggregation and review; some errors from illegible forms, transcription & incomplete registers; limited disaggregation; limited real-time implementation-related corrective action; and requiring a lot of time from staff for the entering of data, verification of the data & writing of reports.

1.3 Aim

The aim of this study is to design, develop and implement a deep-learning (ML) Decision Support System that predicts two main child-health risks, being dropping out of school and suffering stunted growth; using some historic school and health-post data in Zambia.

1.4 Objectives of the study

The objectives of the study are:

1. Identify key educational and health indicators predictive of school-dropout and stunted-growth.
2. Build and evaluate deep-learning classifiers for risk prediction.
3. Assess how dimension tables (e.g. school attendance, health-post records) enhance model performance.
4. Explore practical implications for program implementing partners - NGOs, policymakers and frontline staff.

1.5 Research Objectives

The study is driven by the need to understand and predict two major developmental risks in children: school drop-out and stunted growth. The research is guided by the following questions:

1. What key factors in a child's educational and health background are most predictive of school dropout or stunted growth?
2. Can deep learning models accurately predict whether a child is at risk of dropping out of school or becoming stunted based on available data?
3. How can school and health-post data, as dimension tables, enhance predictive Performance?
4. What are the practical implications of using such predictive models in supporting early interventions by NGOs and education/health policymakers?

1.6 Scope and Limitation

This research focuses on the development of a deep learning-based predictive model that classifies school-aged children as being at risk of

(i) dropping out of school and

(ii) experiencing stunted growth. The data used centers on child-specific attributes (e.g. age, health status, attendance, meals per day), linked to school and health post contextual data.

Scope:

- Geographic focus is on Zambia.
- Children between the ages of 6 and 16.
- Predictive model includes health and education features but excludes socio-economic protections like household income and parental employment due to data sparsity

Limitations:

- Exclusion of financial and parental dimensions may reduce model completeness.
- Data availability and quality may limit generalizability.
- The model does not include longitudinal tracking, limiting trend analysis over time.

1.7 Significance of the Project

The Project introduces a scalable Machine Learning Decision Support System for early prediction and warning of school-dropout and stunted-growth risks, for children between the ages of 6 and 16. This would empower and enable Non-Governmental-Organization programming around the subject concerns, and associated policymakers to run and manage interventions more effectively, strategically and tactfully. This model complements existing Monitoring & Evaluation by providing real-time, automated risk flags, for informed decision-making.

1.8 Preliminary sections of the project report

The preliminary sections of the Project Report are:

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1.9 Chapter Summary

Chapter 1 has outlined the limitations of traditional M&E in child-health protection related programming, and defined the aim and objectives of a proposed Machine Learning-based Decision Support System. There has been a clarification of the study's scope, its significance and structured flow.

LITERATURE REVIEW

2.1 General Background

On a broad overview internationally, the basic needs of a child are their health, clothing, shelter and nutrition, which translate to health and social protection. There have been many projects and initiatives around these concerns, especially for developing countries, and also as a long-term strategy on alleviation of poverty. The projects and initiatives have varied from one aspect of intervention to another, but continue to run and innovate.

Traditional Monitoring and Evaluation Systems have span for quite a period of time. They have over the years evolved through relying on paper-based tools, periodic data collection, and manual aggregation to track inputs, activities, outputs, outcomes and impacts. The birth of this phenomena and science was mostly founded by the needs to:

- Ensure accountability against workplans and budgets
- Measure progress on key indicators
- Informing mid-course correction and donor reporting

Routine Health and Social Protection Information Systems have mostly been about:

- o Facility Registers & Caseworker Logs: for child immunization; growth-monitoring; service referrals; cash/in-kind gesture transfer disbursement ledgers.
- o Monthly/Quarterly Summary Forms: for aggregation of number of visits; treatments; payments; submission upwards (community-to-district-to-national).
- o Supervisory Checklists & Spot-Checks: for verification of accuracy of registers, stock levels, beneficiary lists; and for completion by supervisors during the activities of facility and community visits.

When it comes to Community-Level Monitoring, they have usually encompassed the following:

- o Community Meetings: gathering of verbal updates of service delivery, and any challenges encountered, and beneficiary feedback.
- o Suggestion Boxes & Complaint Registers: The paper forms left at clinics or social protection offices.

The Evaluation Phase of such projects usually cover baseline, midline and endline household surveys through sets of standardized questionnaires & sample designs categorized or determined by the geography, wealth range, and beneficiary status. The evaluations done during the project implementation process are form of some fidelity checks and participation assessments. There are also evaluations of outcomes and impacts, concerned with pre-to-post designs, quasi-experimental methods and key informant interviews & FDGs.

The common Key Indicators of Projects about the Health and Social Protection of Children are:

- Child Health – Under-5 mortality rate; immunization coverage; rate of acute malnutrition.
- Service Delivery – Percentage of inventory of vaccine or therapeutic foods issued out; home-visit coverage.
- Social Protection – Number of targeted households reached; timeliness of cash/in-kind transfers.
- Empowerment & Protection – School-attendance among beneficiary children; reported child safeguarding incidents.

In terms of Reporting and Use, monthly bulletins have often been used for managers, quarterly review meetings with field personnel, local authorities and donors, with lastly, annual impact reports being used against the baseline or endline benchmarks.

2.2 Broad literature review of the topic

This section surveys foundational work and emerging trends in applying machine learning-based decision support systems (ML-DSS) to enhance child health protection and social welfare. It begins with traditional monitoring & evaluation (M&E) approaches,

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then examines how machine learning (ML) and clinical decision support systems (CDSS) have transformed healthcare delivery—culminating in recent pediatric-focused applications that underpin the proposed ML-DSS for predicting school dropout and stunting risks.

2.3 Critical review of related works

Jayatilake & Ganegoda, 2021, covered how Machine Learning (ML) algorithms enhance healthcare decision making. They touched on Machine Learning's ability of analyzing complex medical data, improvement of accuracy and reduction of processing time of diagnostic tasks like detection of diseases and illnesses, and predicting them. What formed as influential factors were: need for early detection of diseases so that treatments could be planned and rendered early; the limitations of human detection being addressed; and the growth of computational biology and precision medicine domains. Their article highlighted how machine learning had evolved from basic processing of data to its current growing application in healthcare, propelled by algorithm and computer power advancements & innovations.

The review discussed how algorithms became enhanced with training, testing and validation, through some features and improved accuracy.

Just as this article, one can rarely delve into machine learning and not meet Supervised and Unsupervised learning; Deep Learning and Neural Networks; Ensemble Methods and Challenges, as the implementation algorithms and techniques of machine learning. They made reference to the popularity of deep learning frameworks, noting tools like Python and TensorFlow as some of the most dominant in healthcare applications.

Machine Learning was stated to analyze medical data for the realization and identification of any patterns that may not be obviously evident to the human eye, in order to predict illnesses and diseases, & to support tailored treatments based on genetics. It was expressed that medical imaging had improved tremendously, and that machine learning algorithms enhanced the procession of images for diagnosis which was very accurate with detecting abnormalities. It was also explained that Machine Learning could be used for the analysis of gene expression, protein-to-protein interactions, algorithm clustering. Machine learning was also said to identify new ways of use for drugs that already exist through biological data analysis and helping in the research of treatment. According to Jayatilake & Ganegoda, 2021, Machine Learning can also be applied in the processes of patient care, allocation of resources and public health policy, noting that in cases of emergency scenarios, good decision making can be rapidly applied. The article showed the application of machine learning in breast cancer detection, heart disease prediction, and the management of hospital resources; as examples of application.

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.

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.

It followed a structured process that was adapted from established guidelines. Google Scholar was used with specific keywords, including “clinical decision support system”, “machine learning”, “pregnancy”; which had resulted in about one thousand and fifty-three (1053) publications, that got filled into the relevant research papers following elimination of non-English articles, non-peer-reviewed works, and the ones that did not specify pregnancy care. The inclusion criteria used by the Authors was that articles were supposed to describe CDSS developed using machine learning in relation to pregnancy care, focusing on the dimensions of diagnosis, prognosis, and treatment. The authors had analysis of their article by two independent reviewers, for the themes of Machine Learning methods, explainability, data sources, and testing.

There were seventeen (17) research papers reviewed, covering CDSSs for different stages of pregnancy, focusing on supporting diagnosis, prognosis and treatment for mothers and babies. Support Vector Machine and Artificial Neural Networks were commonly used. Decision Trees and Random Forests were sparsely found in the work. The trend since 2016 seems to have been towards more complex algorithm models. 23.5% of the studies used explainable (white-box: e.g. decision trees), while the 64.7% majority relied on black-box models (ANN, SVM) – which indicated a gap in making machine learning models interpretable for clinicians.

Most of the studies used data from one center or country, and this limited cultural, ethnic and racial diversity. There wasn't enough discussion of how this could affect generalizability, probably potentially resulting in biased models and a reduction in application.

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Only a few CDSSs were implemented and tested in clinical practice. Impacts like reduced diagnostic errors and workload were reported, but there was generally not enough user testing, external validation, and real-world challenge awareness.

Future work recommendations entailed enhancement of explainability; improvement of data diversity; and focusing on implementation.

Regardless of the gaps, the article emphasized that machine learning-based CDSSs had potential for improving pregnancy care. It encouraged addressing of the challenges by interdisciplinary collaboration and for research to be translated into practice.

Awaysheh et al., 2019, focused on the application of machine learning in medical decision support systems, comparing to historical developments, algorithmic techniques, and practical challenges. They provided a comprehensive review of how machine learning mechanisms helped towards medical decision-making, especially in relation to clinical and diagnostic contexts for veterinary and human medicine. Their review aimed to examine foundations and evolution of computer-based decision support tools, explore and explain archetypal machine learning algorithms like Naïve Bayes, decision trees, and neural networks; as well as discuss the handling of data, its validation and future implications. The authors aimed to emphasize the flexibility of Machine Learning in managing uncertainty in medical diagnoses and treatments, while addressing its application gaps.

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.

Some learning points were that proper data representation and validation were very cardinal for reducing errors and ensuring application of medical decision support in the real world.

The article concluded on machine learning tools having the capability of providing flexibility, accuracy and being able to learn from various and different data sources and therefore exceeding traditional statistical methods.

A recommendation was given that future work should focus on standardized reporting, much bigger data sets and interdisciplinary collaboration for the enhancement of diagnostic tools.

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.

KIDMATCH served as a clinical decision support system, which would help in the diagnosis and treatment of MIS-C and Kawasaki, with them being very serious conditions. The article revealed advanced use of Artificial Intelligence for detection of MIS-C early enough, addressing the challenge of distinguishing it from Kawasaki disease and other febrile illnesses – which clinicians had been encountering.

KIDMATCH model development demonstrated the potential that Artificial Intelligence greatly has, to improve and expand diagnostic accuracy, for the provision of crucial support towards healthcare providers in variation of complicated pediatric conditions.

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.

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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).

Their addition of lab tests resulted in minimal gains, where syndromic only models performed almost equally well. The models performed more ultimately with ruling out disease than detecting it, causing a class imbalance.

The conclusions and recommendations of De Laco et al. were that Prototype Machine Learning Clinical Decision Support Systems could be infused in EHRs or mobile apps for the supporting of clinicians, and to sync real-time surveillance. They also alluded that decision thresholds could be adjusted towards local priorities, like minimization of false negatives versus false positives; and added that the approach was adaptable to other types of infections, especially the ones with rare lab resources. Pertussis was found to be endemic because it weakened immunity and had high rates in the spring-summer season. RSV was found to be a common infection among children up to the age of two (2), with high rates in the autumn-winter season. The mitigation of COVID-19 disturbed typical respiratory-infection patterns and proved the need for Artificial Intelligence-driven pre-syndromic surveillance.

Ravi et al., 2017, explored the concept of Free-Text Preprocessing, through text tokenization, word stemming, controlled-terminology abstraction and stop-word removal. They explained that feature selection matters because very high-dimensional text features could cause overfitting, longer runtimes and very few interpretable models. They had found that choosing a compact subset of only the relevant attributes improved generalization and efficiency.

They agreed with studies that had proven that removal of up to 96% of features usually maintained or enhanced the performance of the model. Their evaluation metrics included AUC, precision-recall, the F-measure of default and best, and geometric and arithmetic mechanisms.

When they compared **Filter** to **Wrapper** method, they concluded that the **Filter** method used data-heavy criteria to drop irrelevant features, and that it is a quicker and classifier-agnostic method that can maintain suboptimal features. Regarding the **Wrapper** method, their conclusion was that it infuses the selection of features inside the learning algorithm's search for best subsets, and tended to produce higher-quality, custom feature sets at the cost of greater computation.

Their findings were a 2010 study of three model types which had reported that performance got improved or remained the same after thorough pruning of features. Another finding of theirs was a 2013 comparison of five algorithms, that had confirmed that reducing 75% of inputs didn't harm but usually assisted classification.

Ba, A., 2021, developed a framework through correlations and regressions, to demonstrate the relationships between M&E System dimensions, Development Management capabilities and overall benefits.

The author significantly linked M&E System Quality, M&E Information Quality, M&E Information Quality and M&E Service Quality. He alluded to a well-designed M&E system requiring clear manuals, defined roles, realistic work plans, and enough resources.

Ba, A., 2021, defined the effectiveness of M&E systems to be factored by utilization of M&E information; high quality of M&E information; and system sustainability. The factors were stated to have the ability to ensure that decision-makers received relevant information for development actions.

Supporting policymaking, improving policy analysis, fostering management of ministries and enhancing transparency and accountability were some of the benefits of effective M&E systems that the author promoted.

The study worked with three iterations, being literature review, case studies, and surveys to analyze the effectiveness of M&E systems. It contributed to Development Management by deepening an understanding of how effective M&E systems enhance policy-making, decision-making, and the ability to expand sustainable development goals.

For future research, there was an urge for in-depth research on different aspects of M&E systems and their impact on development management.

EvalCommunity, 2024, established that continuous operational and tactical adjustments were very important for effective implementation on the basis of feedback from the field and for the purpose of analyzing program outputs and financial inputs. They deemed that adjustments could have been required at the outcome level so that there would be alignment with dynamic economic context and program performance.

The effectiveness of Results-Based Management practices was quantified by models which measured how the practices affected improved policy and program design. The model indicated that RBM accounted for about 29.24% of the difference in enhanced outcomes, signifying its importance in development management.

For the aspect of Evidence-Based Decision Making; it was found that the EBDM practice significantly influenced improved operational decisions, and leading up to about 53.78% of the difference in outcomes. This proved that decision-making based on rigorous evidence was paramount for effective M&E systems.

They went on to allude that enhanced tactical and strategic decisions were driven by collaboration of both Results-Based Management and Evidence-Based-Decision-Making practices, illustrating their significance in the making of informed decisions during the implementations of programs.

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The research made use of a mixed-methods approach, by combination of literature reviews, case studies, and surveys in order to analyze the effectiveness of M&E systems; resulting in them revising the M&E System Effectiveness Framework, covering different dimensions of M&E quality with some development management capabilities and overall advantages.

The study highlighted a need for further research into M&E systems for the improvement of their effectiveness and adoption to different contexts and segments.

Readings, K., 2015, discussed how effective M&E involves explicit definitions of objectives and indicators for progress tracking. The author emphasized the use of leading indicators for measuring progress and performance effectively, explaining that it helps in the assessments of outcomes and impacts in the context of managing projects.

Continuous reflection of program implementation was encouraged and found to be vital for assessing whether projects were on course to fulfill and satisfy their goals, which involved addressing critical questions on anticipated and/or unanticipated effects of the interventions.

The article concluded that understanding and improving M&E practices could lead to more effective decision-making and enhanced project results.

Hermann, C., 1987, touched on the need to understand the processes which link inputs, activities, outputs and outcomes in the management of projects, and that it's very advantageous to identify factors which facilitate or hinder the achievement of planned outcomes. They went on to explain that through leading indicators project managers could weigh processes and make some informed decisions influenced by early signals versus only relying on the final outcomes at the end of the project.

The article encouraged clear logical frameworks to be a profound aspect of effective M&E systems, since they outlined the relationships between important project elements. Apparently, the structure would help in determining causal links and aids in the measurement of progress at various levels and stages, of the implementation.

They found that assessment of indicators of outcomes and impacts were sophisticated because of attribution and measurement, and that using leading indicators helped to address this. Another finding from them was that the lessons learned from evaluations usually lacked generalizability, meaningful context or enough justification. They encouraged continuous improvement in the understanding of knowledge and learning processes to improve the quality of gained insights.

Their conclusion was that focus on pathway analysis, leading indicators, and harnessing a learning culture, organizations could enhance their capability to achieve desired outcomes and adapt to changing circumstances.

Lai, K.C., 2012, went through how designing and validating Management Information Systems ought to include the participation of user communities, project directors, M&E managers and field personnel, stating that the collaborative effort could ensure relevance and manageability of data outputs and propel ownership by stakeholders.

The article discussed how use of Relational Database Management Systems foster integration of static and dynamic data, making possible effective capturing of data, storage and retrieval; noting that the approach supported transaction-based architectures, and enhanced the integrity of data and flexible analysis.

They concluded that it was critically important to integrate effective M&E and MIS frameworks in project management; and that together with fostering participatory approaches, leveraging technology and creating a culture of learning and reflection, the ability to achieve desired outcomes and adapt to new challenges could be enhanced.

2.4 Comparison with related works

In relation to the proposed system, below is a Comparative Analysis of the work that has been reviewed:

Table 1: Comparison with 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	Stemming in free-text analysis	Breadth of coverage Empirically grounded	Predominantly 'classical' ML Sparse treatment of explainable AI

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and architectures in medical decision support systems	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	Real World anchoring via the John Hopkins MediAI example Clear exposition of classic ML techniques	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 minimize bias Prototype easily integratable into EHRs or mobile apps for real-time clinical decision support and syndromic surveillance	Moderate predictive performance Class imbalance favors negative-case predictions Retrospective design No discussion of CDSS integration workflow
Case-study on MediAI , an AI-powered diagnostic system for rare genetic disease at John Hopkins. A methodology primer on core machine-learning pre-processing steps in health informatics.	MediAI system ASI & Ethics Text Preprocessing Feature Selection	Holistic scope Real-world anchoring Empirical grounding Symbolic-statistical fusion	Classical-ML focus Narrow modalities Limited interpretability Sparse clinical evaluation
Development and validation of a comprehensive framework for measuring Monitoring & Evaluation system effectiveness in development settings	DeLone, W.H. & McLean, E.R. (2003); Barton, T. (1997); Bertram, D. (2006); Mackay, K. (2007; 2010); Edmondson, A.C. & McManus, S.E. (2007); Yin, R.K. (2014); Savall, H. & Zardet, V. (2011)	Holistic Framework Rigorous Mixed Methods Validity & Reliability Safeguards Practical Utility Ethical Compliance	Regional Focus Self-Reported Measures Case Selection Bias Sample Size & Scope Implementation Complexity
Development of a practical IS-informed framework for assessing data quality assurance within Monitoring & Evaluation systems in development contexts	DeLone, W.H. & McLean, E.R. (2003); Barton, T. (1997); Bertram, D. (2006); Mackay, K. (2007; 2010); Edmondson,	IS-model integration Comprehensive dimension-set Mixed-methods rigor Practical toolkit Pilot evidence	Limited geography & sectors Tool Inventory skew Benchmark calibration Longitudinal impact unknown Resource Intensity

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	A.C. & McManus, S.E. (2007); Yin, R.K. (2014); Savall, H. & Zardet, V. (2011)		
Monitoring & Evaluation (M &E) as a specialized form of information system applying the DeLone & McLean IS Success model to the world of development programs	DeLone, W.H. & McLean, E.R. (2003); Barton, T. (1997); Yin, R.K. (2014); Edmondson, A.C. & McManus, S.E. (2007); Nicolini, D. (2011); Caldwell, R. (2002); Woodhill, J. (2006)	Holistic Structure Theory-to-Practice Mixed-Methods Foundations Interactive Learning Emphasis on Reflection	Contextual Narrowness Technology Scope Depth vs. Breadth Static Framework Limited Empirical Follow-Up
M&E as a specialized form of information system and offering a structured, context-aware framework for designing effective M&E processes in development programs	Barton, T. (1997); DeLone, W.H. & McLean, E.R. (2003); Edmondson, A.C. & McManus, S.E. (2007); Nicolini, D. (2011); Woodhill, J. (2006)	Holistic IS-lens Issue-Opportunity Mapping Organizational Analysis Emphasis on Learning Rigorous Mixed Methods	Contextual Boundaries Technology Scope Practitioner Accessibility Power & Capacity Gaps Long-Term Validation
Monitoring & Evaluation as a specialized Information System; through diagnosing core design issues, examining organizational arrangements for M&E units, offering a structured, iterative model – to guide more effective M&E/MIS design in development contexts	Barton, T. (1997); DeLone, W.H. & McLean, E.R. (2003); Edmondson, A.C. & McManus, S.E. (2007); Nicolini, D. (2011); Caldwell, R. (2002); Woodhill, J. (2006)	Holistic IS Lens Issue-Opportunity Mapping Organizational Analysis Iterative, Mixed-Method Rigor Emphasis on Reflection & Learning	Context-Specific Examples Limited Digital/Mobile MIS Coverage Practitioner Accessibility Empirical Validation Gaps Political-Economy & Resource Constraints

2.5 Identified Gaps

Jayatilake et al., 2021, highlighted some gaps as follows, regarding common challenges of Machine Learning healthcare decision support:

- **Data Sparsity** – A lot of clinical domains, in the case of rare diseases lacked sufficient and balanced datasets.
- **Expert Disagreement** – Machine Learning-bases usually embedded conflicting expert rules and annotations. Belief-revision systems could boost consensus, and yet had challenges in preserving the credibility of individual expert judgement.
- **Temporal Reasoning** – Modeling how a patient's state evolved during disease progression was limited. Markov decision processes innovated earlier interventions but were very rigid for complicated, and multimodal clinical trajectories.
- **Uncertainty Management** – Clinical data were noisy and not complete and quantifying and propagating uncertainty was significantly under-developed. The existing Bayesian network, Dempster-Shafer theory, Monte Carlo methods helped but it was very challenging to integrate them seamlessly into real-time CDSS pipelines.
- **Logic-Based Reasoning Integration** – Rule-based checks could spot drug interactions or assess symptom severity, but fail to blend well with probabilistic Machine Learning models.
- **Translation to Practice & Evaluation** – Even though Pilot implementations reported tremendous gains in accuracy and time-to-diagnosis, standardized benchmarks and long-term, multi-center trials were rare. There was need for common evaluation protocols, interoperability standards, and clearer regulatory and ethical guidance.

The gaps that Du et al., 2023, established for address by future work were as follows:

- **Lack of Explainability** – Black-box models dominated recent-work, and there was very minimal and limited focus on predictions being made transparent to clinicians.
- **Limited Data Diversity & External Validation** – Most of the models trained on data that was from center or country, with nowhere else to compare performance with. The studies had not explored nor reported cultural, ethnic or racial effects explicitly.
- **Implementation & User Testing Gap** – Very limited CDSS prototypes had been under-taken as software or web applications. There was disconnection between model development and integration with the real world.
- **Applicability & Generalizability Awareness** – The populations on which the models were trained were not adequately described. There was no delineation of settings or patient groups over which a CDSS was safe to use.
- **Persistent Data-Quality Challenges** – Missing data, outliers and severe class imbalance were common in datasets of pregnancy; of which the challenges were hardly addressed systematically, ending up biased or unstable model risks.

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Awaysheh et al., 2019, found some gaps across the engineering of features, model development, validation and deployment as follows:

- **Data Sparsity** – Clinical domains, in the case of rare diseases, lacked adequately-large, and well-organized datasets. Synthetic-data worked like GANs being able to help but having the challenge of non-full-capture of real-world variability.
- **Expert Disagreement** – There having been conflicting rules and annotations from various clinicians that undermined knowledge-based systems.
- **Temporal Reasoning** – The rare capturing of patients' evolving trajectories by the models, and rigid formalisms failing to present complex, multimodal timelines.
- **Uncertainty Quantification & Propagation** – Lack of a unified framework for measuring, propagating and communicating uncertainty in real-time CDSS.
- **Hybrid (Symbolic & Statistical) Reasoning** – Logic-based checks not integrating seamlessly with data-driven machine learning. There having still been a need for the creation of cohesive architecture to blend symbolic inference and probabilistic models.

Lam et al., 2022, in their development and validation of KIDMATCH for distinguishing MIS-C, Kawasaki disease and febrile illnesses identified the following gaps and limitations:

- **Data Sparsity** – Rare-disease cohorts, like MIS-C, in their case were too minimal and imbalanced.
- **Expert Disagreement** – Belief-revision systems reached a high consensus, but were risking highly over critical expert nuances.
- **Temporal Reasoning** – Simple Markov decision models resulted in around 27% of previous interventions, but they fell short of modelling complex, multimodal patient trajectories in the long-run.
- **Uncertainty Management** – Lack of a unified framework for the quantification, propagation and communication of uncertainty, the whole way through, in real-time decision support.
- **Absence of Gold-Standard Diagnostics** – Both MIS-C and Kawasaki did not have an explicit 'gold-standard' test, which complicated performance benchmarking and sensitivity analyses.
- **Handling Missing or Out-of-Distribution Data** – Exclusion of patients with incomplete records due to conformal rejection of 2-5% of cases. More robust imputation or adaptive rejection strategies were required to improve inclusivity.

The Gaps that got identified by De Laco et al., 2023, were as follows:

- **Data Sparsity** – Pediatric datasets for Pertussis and RSV having been small and imbalanced, limiting the generalizability of the model.
- **Expert Disagreement** – Clinicians usually differing on interpretation of symptoms and grading of severity, resulting in some noisy or conflicting labels.
- **Temporal Reasoning** – The models available treated every encounter in isolation and couldn't capture the evolving course of infection.
- **Uncertainty Management** – Lacking a unified framework for the quantification and propagation of uncertainty that arose from noisy lab tests or missing observations.
- **Logic-Based Reasoning Integration** – Rule Based checks not synergized with probabilistic machine learning models.

The main limitations and challenges that Ravi et al., 2017 were as follows:

- **Interpretability of Models** – deep learning models mostly operated as 'black-boxes' therefore making it challenging to comprehend the arrival to results. This challenge posed serious effects on the ability of researchers and practitioners to explain the predictions by models, in clinical settings.
- **Data Requirements** – For deep learning models to be trained effectively they needed large datasets. Electronic health Records were numerous, but unfortunately specific disease data for rare diseases were scarcely available. This posed a limitation in that models could perform efficiently on training data but were failing to generalize to new and unseen data.
- **Preprocessing Needs** – Establishing the ideal preprocessing methods and adjusting hyperparameters was a complex and resource-intensive task which required extensive expertise.
- **Integration of Structured and Unstructured Data** – There was a serious need to integrate insights from structured data effectively. Some potential insights from structured data were overlooked.
- **Methodological Limitations** – Methodologies were not addressing the complexities and unknowns of healthcare data, resulting in revised traditional neural network approaches for improvement of performance and reliability.

Ba A, 2021 identified the following gaps which hinder the efficiency and effectiveness of traditional Monitoring and Evaluation systems:

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- **Limited Understanding of Success Factors** - There having been lack of adequate knowledge of crucial success factors which could contribute to effective M&E systems; crippling the ability to design systems that completely meet developmental objectives of projects.
- **Inadequate Frameworks** – The frameworks for assessment of M&E effectiveness, similar to DeLone and McLean Information System Success Model were not fully capturing some unique complexities of M&E in diverse contexts like developing countries.
- **Poor Data Quality and Availability** - A lot of organizations encountered challenges regarding data quality and timely collection for M&E purposes. There was a great limitation in the effectiveness of decision-making processes that relied on M&E findings.
- **Weak Reporting Systems** – There were ineffective reporting practices which hindered the ability for communication of M&E results into making of decisions, and it eroded the potential of data-driven decision-making.
- **Fragmentation of Information Systems** – M&E systems were often not integrated with other relevant information systems of organizations, therefore causing duplication of efforts and inefficiencies in the management of data.
- **Underutilization of M&E Findings** – Findings were usually not used in a maximized manner when it came to policy-making or program adjustments, and this posed a significant limitation on their impact on project outcomes.

The Gaps found by EvalCommunity, 2024, were as follows:

- **Incomplete Standardization Protocols** – Protocols were outlined but there was no unified standard adoption in all the stages. There were no detailed templates for adaptation according to context-specification.
- **Insufficient Automation in Validation & Cleaning** – There was too much reliance on manual or semi-automated checks, and little to no use of advanced cleaning platforms similar to Artificial Intelligence-based detection of anomalies.
- **Limited Guidance on Metadata & Documentation** – Some standards of Metadata were mentioned, and yet only partially integrated into tools. There wasn't an explicit process for the versioning and maintenance of data dictionaries.
- **Gaps in Real-Time Monitoring & Dashboards** – There was a discussion of dashboards, but without detailed framework for real-time quality-aware systems. Integration of streaming data sources was not addressed.
- **Fragmented Data Governance Structures** – There were no escalation paths for critical quality breaches.
- **Security & Privacy Integration** – Data security and privacy were mentioned but were not integrated with Quality Assurance workflows, similar to automated PII detection.

The gaps and Limitations found by Readings K, 2014, were as follows:

- **Risk of Data Omissions & Weak Planning** – Projects suffered data gaps and weak measurements, due to no well-planned evaluation design and selection of indicators. This compromised the attribution of change to interventions.
- **Weak Adaptive Target-Setting Processes** – There wasn't a structured mechanism for transparent revision in response to resource shifts and external shocks making it possible for poor performance detection to fail.
- **Challenge in Meeting Ideal Indicator Criteria** – Seven mandatory qualities were listed, but there was not much offering on resolution trade-offs when realistic constraints prevent full satisfaction of every criterion.
- **Over-Emphasis on Inputs/Processes Early On** – Early-stage Monitoring & Evaluation prominently focused on inputs and activities with no proper monitoring of exogeneous risks or enabling-environment factors which could enable timely signaling or of derailing projects.
- **No dynamic Framework for Indicator Shifts** – There was lack of a systematic model of timing and operationalizing indicator importance shifts from inputs-to-outputs-to-impacts.
- **Limited Integration of New Technologies & Real-Time Systems** – There was lack of concrete guidance on procurement, system design, or workflow integration for real-time dashboards and alerts.

The gaps that were found by Hermann C, 1987, were as follows:

- **Weak Theory of Change & Logical Framework Alignment**- Outcome chains usually remained implicit and over simplified, posing a challenge to track the linkage of activities and impacts.
- **Fragmented Data Flows & Tool Proliferation** – Several and parallel data collection platforms ended up in creation of silos and redundancy. No proper interoperability hinders timely aggregation and the potential of cross-program learning.
- **Data Quality & Validation Shortcomings** – SOPs regarding data cleaning, validation rules and documentation of metadata were not applied consistently.
- **Minimal Use of Real-Time/Adaptive Monitoring** – Systems were designed on the foundation of periodic surveys and reports instead of continuous and streaming data feeds. There could barely be any rapid feedback loops to trigger course corrections mid-project.

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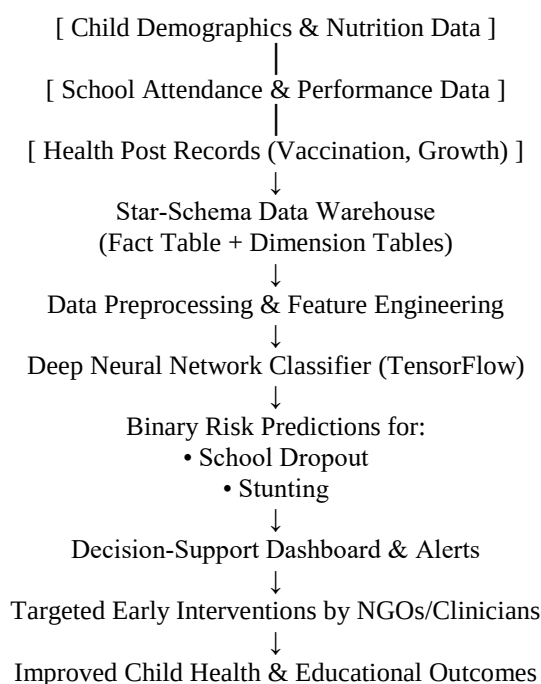
- **Underdeveloped Learning & Knowledge Management Processes** – There was hardly any synthesization of findings into lessons-learned products, and there were no structured forums nor motivation for staff to review M&E results and adapt implementation.

Lai, K.C, 2012 identified the following gaps across projects:

- **Linkages between Baseline and Impact Assessment Surveys** – Majority of surveys were undertaken in form of separate and independent exercises and from various agencies. This resulted in them lacking consistent design, data, methods and analytical processes.
- **Sampling Methodology** – The control samples were too small and vaguely defined, they risked statistical invalidity and some contamination effects.
- **Results Framework and Indicator Specification** – The results and log frames were inadequate and confusing, where the outputs got mis-specified as outcomes, and the intermediate outcome statements and measurable indicators were missing.
- **Missed Methodological Innovations** – There was very limited use of combined methods, where qualitative and participatory tools were under-utilized and didn't fulfill the purpose of quantitative surveys.

2.6 CONCEPTUAL FRAMEWORK/THEORETICAL FRAMEWORK

Diagram (textual flow):



Key constructs and relationships:

- **Inputs:**
 - Child-level fact table (demographics, meals/day, vaccination status, stunted/dropout flags)
 - Dimensions: School (attendance rate, distance, performance), Health_Post (service availability, distance)
- **Process:**
 - ETL into star schema → cleaning, encoding, normalization → feedforward neural network → binary classification
- **Outputs:**
 - Risk scores and categorical alerts for dropout and stunting

Outcomes:

- Data-driven, timely allocation of nutrition support, retention programs, follow-up visits

THEORETICAL FRAMEWORK

To ground both **system design** and **evaluation**, three complementary theories are adopted:

Theory of Change (ToC)

- **Inputs:** Data infrastructure, ML model, stakeholder training
- **Activities:** Model training/evaluation; dashboard deployment; staff capacity-building
- **Outputs:** Automated risk predictions; decision-support alerts

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- **Short-term Outcomes:** NGOs, health-post staff and school staff deliver targeted interventions
- **Long-term Impact:** Reduced stunting rates; improved school retention; strengthened child-health protection
- **Assumptions:** Sufficient data quality; organizational buy-in; and availability of intervention resources

2.7 Proposed model/system

The proposed system is a predictive framework based on a star-schema database architecture. At its center is a fact table containing child-level data. Dimension tables include school (capturing attendance, performance level, distance) and health_post (capturing vaccination, stunted status, distance to facility).

Originally, a parent dimension and a financial-social layer were planned. However, these have been removed due to challenges in collection of reliable data and integration. This aligns with recent literature which suggests that deep learning models can still perform well using minimal but high-quality features (Jiang et al., 2021).

The model architecture will be a deep-learning neural network using TensorFlow, designed to perform binary classification for:

- **Dropout risk:** Whether a child is likely to drop out of school.
- **Stunting risk:** Whether a child is likely to suffer from stunted growth

The System will be trained and evaluated on historical data collected from NGOs and schools, and designed for practical deployment to inform early interventions.

2.8 Chapter Summary

Chapter 2 reviewed related works, analyzed identification of gaps, explored conceptual and theoretical frameworks for the study and modeled a proposed system.

METHODOLOGY

3.1 Research design

The software development method employed in this project is the Rapid Application Development model, that is good at quick developmental cycles, especially when the time resource is not much or is already constrained. Through this methodology, effort was prioritized towards development of a prototype and improving it progressively, rather than spending a lot of effort in preliminary planning of the project. There wasn't a team involved, so everything depended solely on the Research Candidate.

The flow of the work was similar to this sequence:

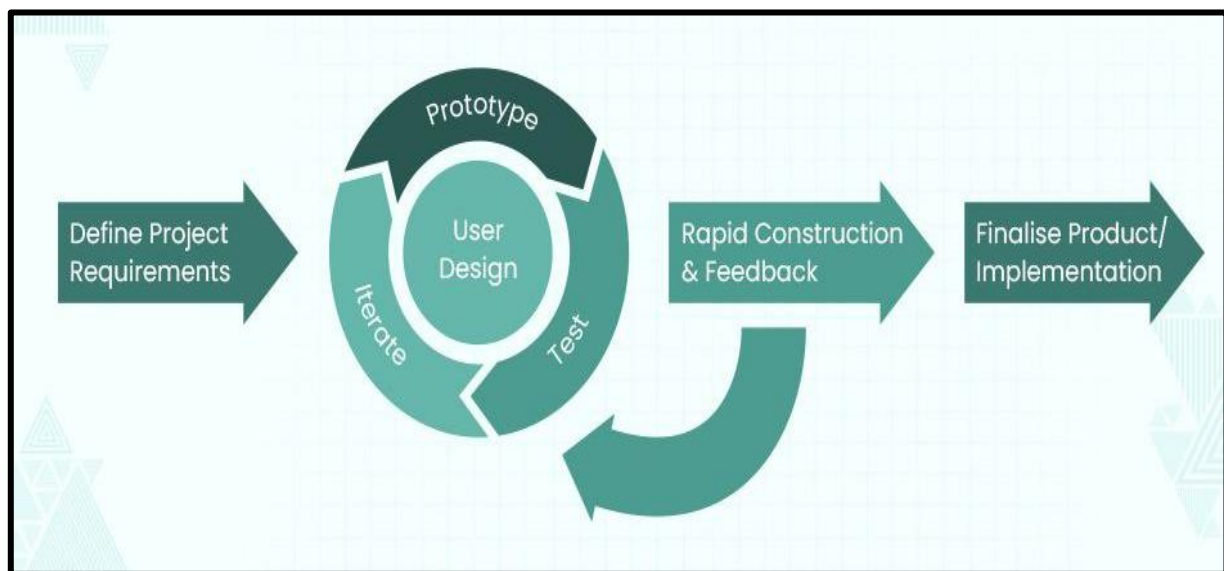


Figure 1. The RAD Software Development Methodology Flow of Activities

The prediction framework was designed and developed according to the following star-schema a database structure:

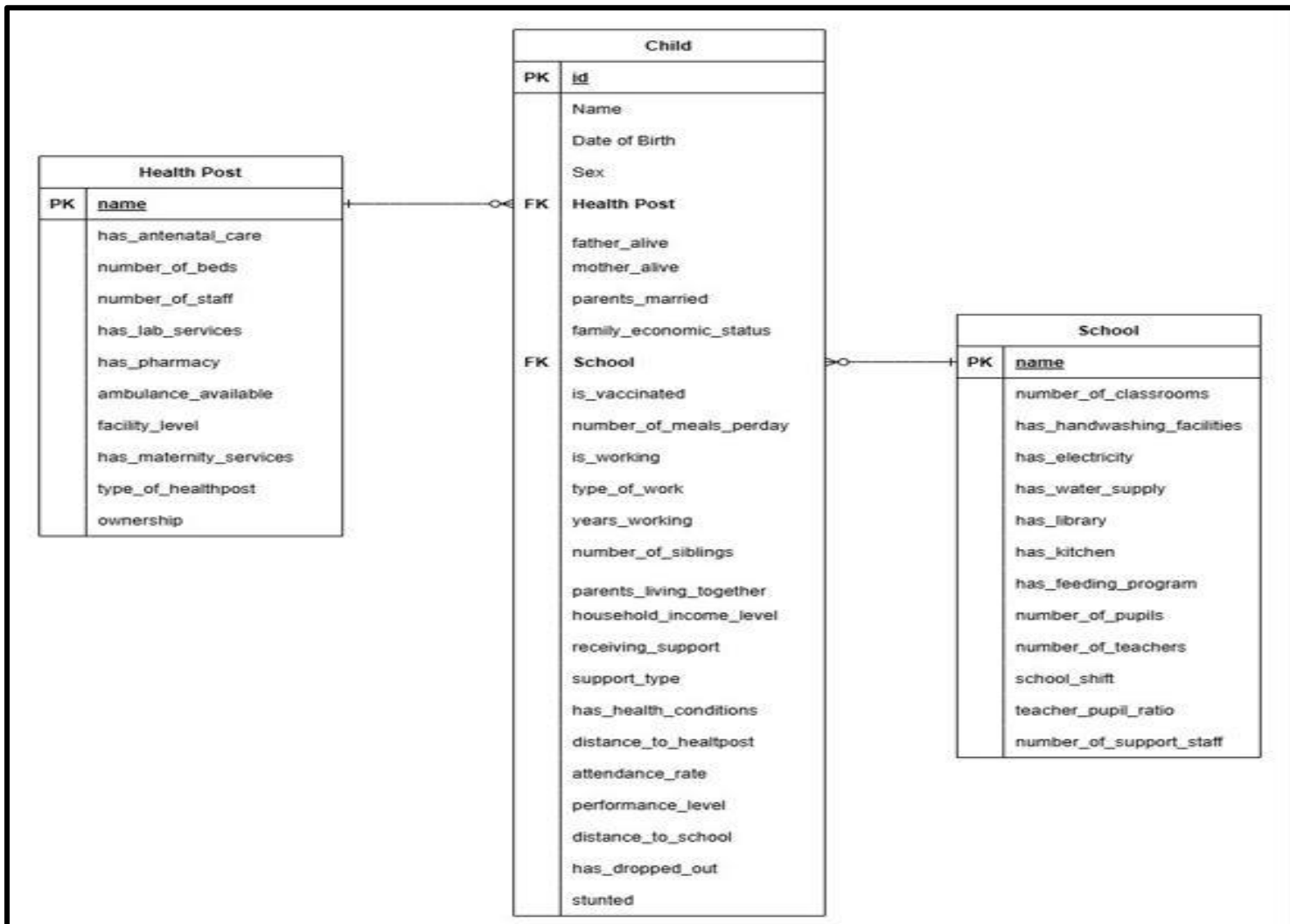


Figure 1. Entity Relationship Diagram of the Fact and Dimensional Tables

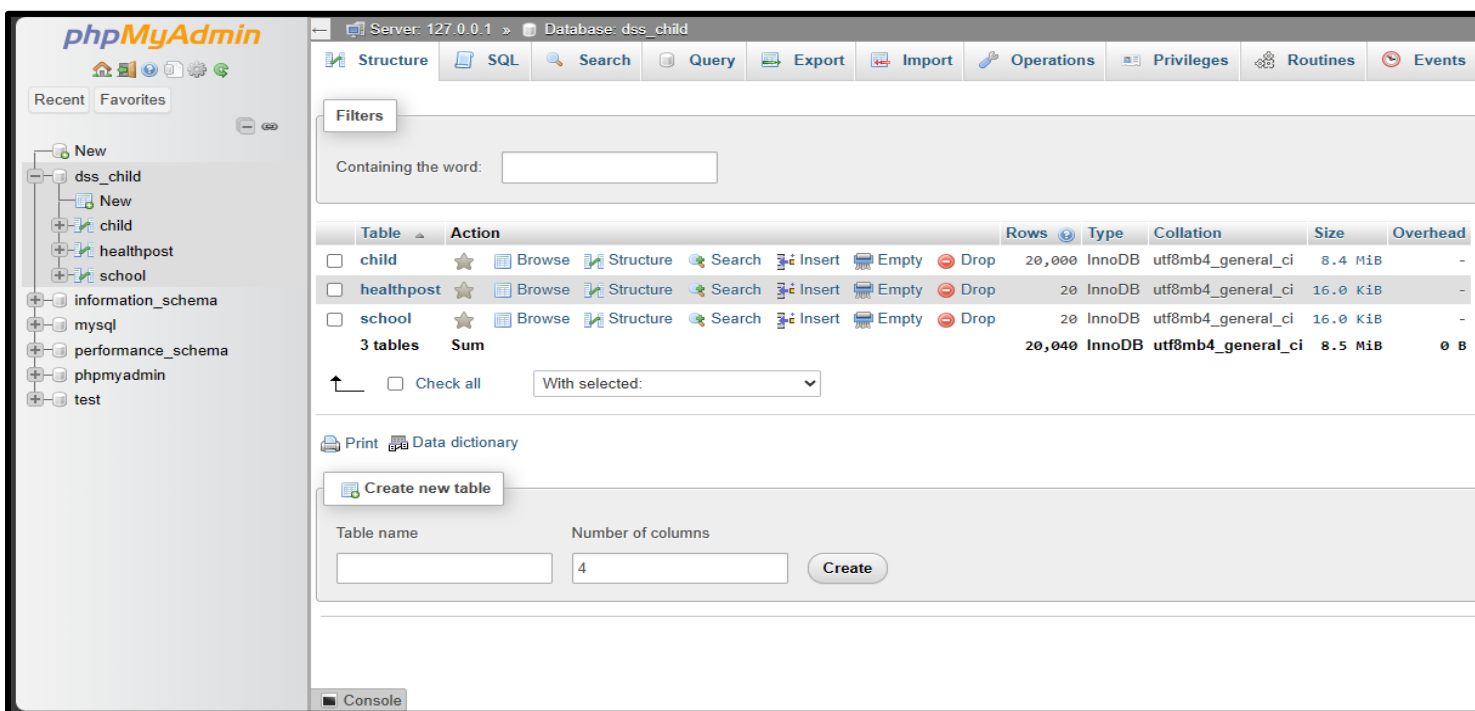


Figure 2. Database View

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Server: 127.0.0.1 » Database: dss_child » Table: child

Showing rows 0 - 24 (20000 total, Query took 0.0044 seconds.)

SELECT * FROM `child`

1 > >> Number of rows: 25 Filter rows: Search this table Sort by key: None

	id	Name	age	Sex	father_alive	mother_alive	parents_married	family_economic_status	is_vaccinated	number_of_me
☐ Edit Copy Delete	1	Latoya Dunn	6	Male	0	0	0	Vulnerable	0	
☐ Edit Copy Delete	2	Erin Cook	6	Female	0	0	0	Vulnerable	0	
☐ Edit Copy Delete	3	Jeremy Jenkins	15	Female	0	0	0	Poor	0	
☐ Edit Copy Delete	4	Mark Ramirez	9	Male	0	0	0	Vulnerable	0	
☐ Edit Copy Delete	5	Kevin Butler	8	Female	0	0	0	Poor	0	

Figure 3. Child Table Structure

Server: 127.0.0.1 » Database: dss_child » Table: healthpost

Showing rows 0 - 19 (20 total, Query took 0.0008 seconds.)

SELECT * FROM `healthpost`

Show all Number of rows: 25 Filter rows: Search this table Sort by key: None

	name	has_antenatal_care	number_of_beds	number_of_staff	has_lab_services	has_pharmacy	ambulance_available	fac
☐ Edit Copy Delete	Chawama Community Health	0	4	5	0	1	0	Lev
☐ Edit Copy Delete	Chibombo Rural Clinic	1	8	12	1	1	1	Lev
☐ Edit Copy Delete	Chisamba Health Post	0	3	4	0	0	0	Lev
☐ Edit Copy Delete	Hope Medical Centre	1	15	25	1	1	1	Lev
☐ Edit Copy Delete	Kabwe North Health Post	1	6	10	1	1	0	Lev

Figure 4. Health_Post Table Structure

Showing rows 0 - 19 (20 total, Query took 0.0007 seconds.)

```
SELECT * FROM `school`
```

Number of rows: 25 Filter rows: Search this table Sort by key: None

	name	number_of_classrooms	has_handwashing_facilities	has_electricity	has_water_supply	has_library	has_kitchen
☐	Chama South School	5	0	0	0	0	0
☐	Chelstone Basic School	13	1	1	1	1	1
☐	Chilenje Basic School	10	1	1	1	1	1
☐	Chipata West School	3	0	0	0	0	0
☐	Chongwe Hills School	4	0	1	0	0	0
☐	Kabwe East School	11	1	1	1	1	1

Figure 5. School Table Structure

3.2 Adopted method and justification

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.

3.3 Association of research method to project

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.

3.4 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): demographics, meals, attendance, vaccination, stunted status, dropout status.
- school (dimension): school name, shift type, teacher-pupil ratio.
- health_post (dimension): 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.

3.5 Data collection methods and data analysis techniques

Data collection:

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

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

3.6 Ethical concerns related to the research

Some of the ethical concerns which affect the Research are as follows:

Informed Consent - Ensuring children's guardians (and when appropriate, the children themselves) understand and agree to data collection and model use.

Privacy & Confidentiality - Anonymization of child identifiers and sensitive attributes, and enforced security through secure storage (encrypted databases) and strict access controls to prevent unauthorized disclosure.

Data Ownership & Sharing - Clarifying who owns the data (NGOs, schools, health posts) and under what conditions it may be shared or reused.

Bias, Fairness & Equity - Risk of algorithmic bias disproportionately affecting certain groups (e.g., by region, gender, or socioeconomic status).

Human-in-the-Loop Safeguards - Preventing over-reliance on automated alerts: requiring expert validation before intervention; and the training of field staff to interpret model outputs responsibly.

Regulatory & Cultural Compliance – Alignment of data practices with Zambian child protection laws, data-protection policies (akin to GDPR), and cultural norms around minors.

SUMMARY

This chapter unraveled the ML-driven research methodology, particularly supervised learning through (deep-learning) neural networks. It included data sourcing, preprocessing, feature engineering, model architecture, the training/evaluation protocols involved, and associated ethical safeguards. The rigorous approach underpins the system's design and conforms to the project's objective of building predictive classifiers for child-health risks in Zambia.

PROTOTYPE, DATA, EXPERIMENTS, AND IMPLEMENTATION

4.1 Appropriate modelling in relation to project

The objective of the project is to develop a decision support system that can predict whether a child is at risk of dropping out of school or suffering from stunted growth based on household, educational, and health data. Given the binary nature of both prediction tasks, Artificial Neural Networks (ANNs) were used for the primary modelling technique, due to their ability to capture complex, nonlinear relationships within multidimensional datasets. A separate ANN was developed for each classification task to ensure target and maximize optimization & clearer interpretability.

4.2 Techniques, algorithms, mechanisms

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. 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.

4.3 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 in pyramid-shaped, with the first layer as the number of input features and the subsequent layers being the previous number divided by two.

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- 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.

4.4 Highlight the main functions, models, frameworks, etc to answer the objectives.

The implementation consists of several critical components:

- **Data Extraction and Preprocessing:** Data was extracted from a MySQL database by joining the child, health_post, and school tables. Redundant or non-informative features (e.g., names, IDs) were removed. Categorical columns such as gender, income level, and type of work were label-encoded. All features were standardized using StandardScaler.
- **Model Functions:**
 - ANN Construction: Defined using tf.keras.models.Sequential, with multiple dense layers.
 - Training and Evaluation: Models were compiled with adam optimizer and trained using the .fit() method. Accuracy scores and confusion matrices were used to evaluate performance.
 - Prediction: Predictions on the test set were thresholded at 0.5. Confusion matrices provided insight into true positives versus false positives, etc.
- **Frameworks and Libraries:**
 - **TensorFlow:** For building and training neural networks.
 - **Scikit-learn:** For preprocessing, splitting, and evaluating.
 - **Pandas** and **NumPy:** For data handling and transformations.
 - **SQLAlchemy** and **PyMySQL:** For connecting to and querying the MySQL database.
 - **Joblib:** For saving models and scalers.

These tools worked together to fulfill the project's objectives of automating dropout and stunting risk prediction from structured child-related datasets.

4.5 Chapter Summary

This chapter documents the entire implementation process:

- **Data Preparation:** Connected to a MySQL database and joined relevant tables. Cleaned and encoded categorical variables, then scaled numeric features using StandardScaler.
- **Model Architecture:** Two separate multi-layer perceptron models with ReLU activations in hidden layers and sigmoid output for binary classification.
- **Training:** Each ANN was trained for 100 epochs using a batch size of 1000. The models were evaluated using accuracy and confusion matrices on unseen test data.
- **Evaluation:** While current metrics are limited to accuracy and confusion matrix, the structure allows for inclusion of precision, recall, and AUC in future versions.
- **Tools:** Python (with TensorFlow, Scikit-learn, Pandas), MySQL (via SQLAlchemy), and joblib for model persistence.

RESULTS AND DISCUSSIONS

5.1 Results Presentation

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

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- 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.

5.2 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.
- 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 will provide better insight into how well the model balances risk of over- and under- prediction.

5.3 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 these 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**).

5.4 Implications of Results

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

1. **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.
2. **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.
3. **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.
4. **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.

5.5 Chapter Summary

This chapter presents and discusses findings, as follows:

- **Model performance metrics** for both dropout and stunting predictions.
- **Confusion matrices** illustrating the models' classification ability.
- Although ROC curves and feature importance were not visualized in this iteration, it would be paramount for future development to include:
 - ROC curves to better measure sensitivity vs specificity trade-offs.
 - Feature importance analysis to highlight key drivers (e.g., meals per day and attendance rate correlated with dropout risk).
- A **discussion of false positives and negatives**, noting how these impact real-world applicability of the models.

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- **Contextualization within Zambia's education and health landscape**, showing how predictive outputs can inform and influence targeted interventions and strengthen NGO program design.

SUMMARY AND CONCLUSION

6.1 Summary of Main Findings

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 incorporate 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.

6.2 Discussion and Implications in Relation to Objectives

Early warning would be made possible, through some automated risk flags that would readily enable field staff to prioritize assessments. Implementing NGOs and partners (health post staff and school staff) would be in a better position of strategizing support, by perhaps prioritizing the e.g. feeding programs, psychosocial support, and follow-up visits to more vulnerable children or those at higher risk of dropping out of school or stunting.

In order to mitigate false positives and false negatives, the model outputs could be combined with human involvement and collaboration of community feedback & expert validation.

6.3 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.

6.4 Limitations of the system/model/framework

- Absence of detailed household financial data may reduce prediction accuracy for economic-driven dropout.
- Lack of longitudinal data limits trend-based predictions.
- Generalizability is limited due to geographic and sampling constraints.

6.5 Future works

- ✓ Integrate parental, household, and social protection data where available.
- ✓ Explore time-series deep learning models (e.g., LSTM) for tracking changes over time.
- ✓ Deploy the model in a live NGO system and evaluate its real-world impact.

6.6 Chapter Summary

Chapter 6 closes by underscoring the promise of marrying robust data architectures, deep learning, and participatory evaluation to strengthen child-health protection, while calling for iterative refinement, ethical vigilance, and stakeholder co-ownership as the system moves toward real-world deployment.

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APPENDICES

Appendix A MODEL TRAINING RESULTS

Model results:

```
%runfile C:/AI/DSS-CHILD/ModelTraining.py --wdir
```

Setting the working directory.....

Importing the libraries.....

2025-06-30 09:14:16.930378: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF\_ENABLE\_ONEDNN\_OPTS=0`.

2025-06-30 09:14:18.361455: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF\_ENABLE\_ONEDNN\_OPTS=0`.

Connecting to the database.....

Database URL: mysql+pymysql://root:***@localhost:3306/dss_child

Driver: pymysql

Dialect: mysql

Host: localhost

Port: 3306

Username: root

Database Name: dss_child

Connection successful.

Data collected

Data Preprocessing.....

Splitting the dataset into the Training set and Test set.....

Feature Scaling.....

2025-06-30 09:14:23.095943: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.

To enable the following instructions: SSE3 SSE4.1 SSE4.2 AVX AVX2 AVX_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.

Creating the Dropout ANN.....

Creating the Stunted ANN.....

Done

Training the Dropout ANN.....

Epoch 1/100

4/4 ————— 1s 9ms/step - accuracy: 0.7484 - loss: 0.5611

Epoch 2/100

4/4 ————— 0s 5ms/step - accuracy: 0.7463 - loss: 0.5045

Epoch 3/100

4/4 ————— 0s 6ms/step - accuracy: 0.7587 - loss: 0.4626

Epoch 4/100

4/4 ————— 0s 6ms/step - accuracy: 0.7554 - loss: 0.4436

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Epoch 5/100
4/4 ————— 0s 6ms/step - accuracy: 0.7597 - loss: 0.4243

Epoch 6/100
4/4 ————— 0s 6ms/step - accuracy: 0.7572 - loss: 0.4184

Epoch 7/100
4/4 ————— 0s 6ms/step - accuracy: 0.7692 - loss: 0.4039

Epoch 8/100
4/4 ————— 0s 6ms/step - accuracy: 0.7687 - loss: 0.3871

Epoch 9/100
4/4 ————— 0s 6ms/step - accuracy: 0.7700 - loss: 0.3896

Epoch 10/100
4/4 ————— 0s 6ms/step - accuracy: 0.7617 - loss: 0.3886

Epoch 11/100
4/4 ————— 0s 6ms/step - accuracy: 0.7650 - loss: 0.3775

Epoch 12/100
4/4 ————— 0s 6ms/step - accuracy: 0.7633 - loss: 0.3755

Epoch 13/100
4/4 ————— 0s 6ms/step - accuracy: 0.7699 - loss: 0.3676

Epoch 14/100
4/4 ————— 0s 6ms/step - accuracy: 0.7665 - loss: 0.3703

Epoch 15/100
4/4 ————— 0s 6ms/step - accuracy: 0.7721 - loss: 0.3663

Epoch 16/100
4/4 ————— 0s 4ms/step - accuracy: 0.7706 - loss: 0.3593

Epoch 17/100
4/4 ————— 0s 4ms/step - accuracy: 0.7775 - loss: 0.3569

Epoch 18/100
4/4 ————— 0s 4ms/step - accuracy: 0.7829 - loss: 0.3521

Epoch 19/100
4/4 ————— 0s 4ms/step - accuracy: 0.7784 - loss: 0.3557

Epoch 20/100
4/4 ————— 0s 4ms/step - accuracy: 0.7769 - loss: 0.3521

Epoch 21/100
4/4 ————— 0s 6ms/step - accuracy: 0.7832 - loss: 0.3509

Epoch 22/100
4/4 ————— 0s 6ms/step - accuracy: 0.7885 - loss: 0.3457

Epoch 23/100
4/4 ————— 0s 6ms/step - accuracy: 0.7861 - loss: 0.3468

Epoch 24/100
4/4 ————— 0s 6ms/step - accuracy: 0.7871 - loss: 0.3435

Epoch 25/100
4/4 ————— 0s 6ms/step - accuracy: 0.7857 - loss: 0.3446

Epoch 26/100
4/4 ————— 0s 5ms/step - accuracy: 0.7896 - loss: 0.3417

Epoch 27/100
4/4 ————— 0s 6ms/step - accuracy: 0.8025 - loss: 0.3379

Epoch 28/100
4/4 ————— 0s 6ms/step - accuracy: 0.7896 - loss: 0.3436

Epoch 29/100
4/4 ————— 0s 6ms/step - accuracy: 0.7962 - loss: 0.3382

Epoch 30/100
4/4 ————— 0s 6ms/step - accuracy: 0.7997 - loss: 0.3335

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Epoch 31/100
4/4 ————— 0s 6ms/step - accuracy: 0.7976 - loss: 0.3421

Epoch 32/100
4/4 ————— 0s 6ms/step - accuracy: 0.8050 - loss: 0.3333

Epoch 33/100
4/4 ————— 0s 4ms/step - accuracy: 0.8054 - loss: 0.3331

Epoch 34/100
4/4 ————— 0s 4ms/step - accuracy: 0.8038 - loss: 0.3352

Epoch 35/100
4/4 ————— 0s 6ms/step - accuracy: 0.8045 - loss: 0.3315

Epoch 36/100
4/4 ————— 0s 6ms/step - accuracy: 0.8071 - loss: 0.3266

Epoch 37/100
4/4 ————— 0s 6ms/step - accuracy: 0.8131 - loss: 0.3229

Epoch 38/100
4/4 ————— 0s 7ms/step - accuracy: 0.8081 - loss: 0.3297

Epoch 39/100
4/4 ————— 0s 5ms/step - accuracy: 0.8151 - loss: 0.3268

Epoch 40/100
4/4 ————— 0s 4ms/step - accuracy: 0.8151 - loss: 0.3245

Epoch 41/100
4/4 ————— 0s 6ms/step - accuracy: 0.8126 - loss: 0.3290

Epoch 42/100
4/4 ————— 0s 6ms/step - accuracy: 0.8171 - loss: 0.3207

Epoch 43/100
4/4 ————— 0s 4ms/step - accuracy: 0.8194 - loss: 0.3220

Epoch 44/100
4/4 ————— 0s 4ms/step - accuracy: 0.8163 - loss: 0.3226

Epoch 45/100
4/4 ————— 0s 6ms/step - accuracy: 0.8193 - loss: 0.3219

Epoch 46/100
4/4 ————— 0s 6ms/step - accuracy: 0.8158 - loss: 0.3241

Epoch 47/100
4/4 ————— 0s 6ms/step - accuracy: 0.8215 - loss: 0.3186

Epoch 48/100
4/4 ————— 0s 4ms/step - accuracy: 0.8197 - loss: 0.3171

Epoch 49/100
4/4 ————— 0s 4ms/step - accuracy: 0.8178 - loss: 0.3159

Epoch 50/100
4/4 ————— 0s 4ms/step - accuracy: 0.8238 - loss: 0.3161

Epoch 51/100
4/4 ————— 0s 6ms/step - accuracy: 0.8198 - loss: 0.3184

Epoch 52/100
4/4 ————— 0s 6ms/step - accuracy: 0.8262 - loss: 0.3164

Epoch 53/100
4/4 ————— 0s 4ms/step - accuracy: 0.8301 - loss: 0.3096

Epoch 54/100
4/4 ————— 0s 4ms/step - accuracy: 0.8327 - loss: 0.3130

Epoch 55/100
4/4 ————— 0s 4ms/step - accuracy: 0.8358 - loss: 0.3085

Epoch 56/100
4/4 ————— 0s 6ms/step - accuracy: 0.8279 - loss: 0.3154

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Epoch 57/100
4/4 ————— 0s 6ms/step - accuracy: 0.8315 - loss: 0.3056

Epoch 58/100
4/4 ————— 0s 6ms/step - accuracy: 0.8335 - loss: 0.3093

Epoch 59/100
4/4 ————— 0s 6ms/step - accuracy: 0.8393 - loss: 0.3093

Epoch 60/100
4/4 ————— 0s 4ms/step - accuracy: 0.8325 - loss: 0.3105

Epoch 61/100
4/4 ————— 0s 4ms/step - accuracy: 0.8367 - loss: 0.3079

Epoch 62/100
4/4 ————— 0s 6ms/step - accuracy: 0.8376 - loss: 0.3026

Epoch 63/100
4/4 ————— 0s 6ms/step - accuracy: 0.8350 - loss: 0.3083

Epoch 64/100
4/4 ————— 0s 6ms/step - accuracy: 0.8406 - loss: 0.3018

Epoch 65/100
4/4 ————— 0s 4ms/step - accuracy: 0.8449 - loss: 0.2988

Epoch 66/100
4/4 ————— 0s 4ms/step - accuracy: 0.8395 - loss: 0.3010

Epoch 67/100
4/4 ————— 0s 6ms/step - accuracy: 0.8472 - loss: 0.2929

Epoch 68/100
4/4 ————— 0s 6ms/step - accuracy: 0.8468 - loss: 0.3038

Epoch 69/100
4/4 ————— 0s 6ms/step - accuracy: 0.8490 - loss: 0.2986

Epoch 70/100
4/4 ————— 0s 3ms/step - accuracy: 0.8500 - loss: 0.2981

Epoch 71/100
4/4 ————— 0s 4ms/step - accuracy: 0.8494 - loss: 0.2981

Epoch 72/100
4/4 ————— 0s 6ms/step - accuracy: 0.8513 - loss: 0.2950

Epoch 73/100
4/4 ————— 0s 6ms/step - accuracy: 0.8505 - loss: 0.2954

Epoch 74/100
4/4 ————— 0s 6ms/step - accuracy: 0.8490 - loss: 0.2978

Epoch 75/100
4/4 ————— 0s 4ms/step - accuracy: 0.8509 - loss: 0.2934

Epoch 76/100
4/4 ————— 0s 4ms/step - accuracy: 0.8526 - loss: 0.2955

Epoch 77/100
4/4 ————— 0s 4ms/step - accuracy: 0.8536 - loss: 0.2911

Epoch 78/100
4/4 ————— 0s 4ms/step - accuracy: 0.8511 - loss: 0.2949

Epoch 79/100
4/4 ————— 0s 6ms/step - accuracy: 0.8523 - loss: 0.2888

Epoch 80/100
4/4 ————— 0s 6ms/step - accuracy: 0.8597 - loss: 0.2848

Epoch 81/100
4/4 ————— 0s 6ms/step - accuracy: 0.8588 - loss: 0.2882

Epoch 82/100
4/4 ————— 0s 4ms/step - accuracy: 0.8592 - loss: 0.2887

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Epoch 83/100

4/4 ————— 0s 4ms/step - accuracy: 0.8606 - loss: 0.2815

Epoch 84/100

4/4 ————— 0s 4ms/step - accuracy: 0.8640 - loss: 0.2846

Epoch 85/100

4/4 ————— 0s 4ms/step - accuracy: 0.8659 - loss: 0.2836

Epoch 86/100

4/4 ————— 0s 4ms/step - accuracy: 0.8683 - loss: 0.2804

Epoch 87/100

4/4 ————— 0s 4ms/step - accuracy: 0.8678 - loss: 0.2802

Epoch 88/100

4/4 ————— 0s 6ms/step - accuracy: 0.8664 - loss: 0.2847

Epoch 89/100

4/4 ————— 0s 6ms/step - accuracy: 0.8686 - loss: 0.2773

Epoch 90/100

4/4 ————— 0s 6ms/step - accuracy: 0.8650 - loss: 0.2799

Epoch 91/100

4/4 ————— 0s 6ms/step - accuracy: 0.8707 - loss: 0.2749

Epoch 92/100

4/4 ————— 0s 5ms/step - accuracy: 0.8682 - loss: 0.2779

Epoch 93/100

4/4 ————— 0s 6ms/step - accuracy: 0.8695 - loss: 0.2746

Epoch 94/100

4/4 ————— 0s 6ms/step - accuracy: 0.8681 - loss: 0.2753

Epoch 95/100

4/4 ————— 0s 10ms/step - accuracy: 0.8685 - loss: 0.2757

Epoch 96/100

4/4 ————— 0s 8ms/step - accuracy: 0.8754 - loss: 0.2712

Epoch 97/100

4/4 ————— 0s 6ms/step - accuracy: 0.8696 - loss: 0.2692

Epoch 98/100

4/4 ————— 0s 6ms/step - accuracy: 0.8630 - loss: 0.2737

Epoch 99/100

4/4 ————— 0s 8ms/step - accuracy: 0.8790 - loss: 0.2714

Epoch 100/100

4/4 ————— 0s 6ms/step - accuracy: 0.8788 - loss: 0.2668

125/125 ————— 0s 1ms/step - accuracy: 0.8768 - loss: 0.2681

Training Accuracy: 87%

Training the Stunted ANN.....

Epoch 1/100

4/4 ————— 1s 6ms/step - accuracy: 0.6072 - loss: 0.6518

Epoch 2/100

4/4 ————— 0s 10ms/step - accuracy: 0.7462 - loss: 0.5649

Epoch 3/100

4/4 ————— 0s 5ms/step - accuracy: 0.7504 - loss: 0.5028

Epoch 4/100

4/4 ————— 0s 10ms/step - accuracy: 0.7515 - loss: 0.4631

Epoch 5/100

4/4 ————— 0s 6ms/step - accuracy: 0.7634 - loss: 0.4243

Epoch 6/100

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4/4 ————— 0s 6ms/step - accuracy: 0.7545 - loss: 0.4188
Epoch 7/100
4/4 ————— 0s 6ms/step - accuracy: 0.7625 - loss: 0.4019
Epoch 8/100
4/4 ————— 0s 6ms/step - accuracy: 0.7635 - loss: 0.3917
Epoch 9/100
4/4 ————— 0s 9ms/step - accuracy: 0.7552 - loss: 0.3941
Epoch 10/100
4/4 ————— 0s 6ms/step - accuracy: 0.7603 - loss: 0.3866
Epoch 11/100
4/4 ————— 0s 6ms/step - accuracy: 0.7668 - loss: 0.3774
Epoch 12/100
4/4 ————— 0s 6ms/step - accuracy: 0.7656 - loss: 0.3747
Epoch 13/100
4/4 ————— 0s 8ms/step - accuracy: 0.7680 - loss: 0.3723
Epoch 14/100
4/4 ————— 0s 6ms/step - accuracy: 0.7630 - loss: 0.3764
Epoch 15/100
4/4 ————— 0s 6ms/step - accuracy: 0.7739 - loss: 0.3621
Epoch 16/100
4/4 ————— 0s 4ms/step - accuracy: 0.7699 - loss: 0.3699
Epoch 17/100
4/4 ————— 0s 6ms/step - accuracy: 0.7700 - loss: 0.3633
Epoch 18/100
4/4 ————— 0s 6ms/step - accuracy: 0.7729 - loss: 0.3635
Epoch 19/100
4/4 ————— 0s 9ms/step - accuracy: 0.7759 - loss: 0.3639
Epoch 20/100
4/4 ————— 0s 6ms/step - accuracy: 0.7833 - loss: 0.3575
Epoch 21/100
4/4 ————— 0s 8ms/step - accuracy: 0.7871 - loss: 0.3555
Epoch 22/100
4/4 ————— 0s 6ms/step - accuracy: 0.7784 - loss: 0.3580
Epoch 23/100
4/4 ————— 0s 6ms/step - accuracy: 0.7877 - loss: 0.3505
Epoch 24/100
4/4 ————— 0s 4ms/step - accuracy: 0.7916 - loss: 0.3534
Epoch 25/100
4/4 ————— 0s 6ms/step - accuracy: 0.7951 - loss: 0.3499
Epoch 26/100
4/4 ————— 0s 4ms/step - accuracy: 0.7923 - loss: 0.3538
Epoch 27/100
4/4 ————— 0s 4ms/step - accuracy: 0.7976 - loss: 0.3503
Epoch 28/100
4/4 ————— 0s 6ms/step - accuracy: 0.8035 - loss: 0.3475
Epoch 29/100
4/4 ————— 0s 6ms/step - accuracy: 0.7984 - loss: 0.3455
Epoch 30/100
4/4 ————— 0s 4ms/step - accuracy: 0.7960 - loss: 0.3505
Epoch 31/100
4/4 ————— 0s 6ms/step - accuracy: 0.7981 - loss: 0.3438
Epoch 32/100

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

4/4 ————— 0s 6ms/step - accuracy: 0.8052 - loss: 0.3467
Epoch 33/100
4/4 ————— 0s 6ms/step - accuracy: 0.8062 - loss: 0.3429
Epoch 34/100
4/4 ————— 0s 6ms/step - accuracy: 0.7977 - loss: 0.3495
Epoch 35/100
4/4 ————— 0s 6ms/step - accuracy: 0.8137 - loss: 0.3350
Epoch 36/100
4/4 ————— 0s 6ms/step - accuracy: 0.8061 - loss: 0.3428
Epoch 37/100
4/4 ————— 0s 6ms/step - accuracy: 0.8063 - loss: 0.3401
Epoch 38/100
4/4 ————— 0s 6ms/step - accuracy: 0.8113 - loss: 0.3327
Epoch 39/100
4/4 ————— 0s 7ms/step - accuracy: 0.8110 - loss: 0.3364
Epoch 40/100
4/4 ————— 0s 8ms/step - accuracy: 0.8127 - loss: 0.3349
Epoch 41/100
4/4 ————— 0s 6ms/step - accuracy: 0.8138 - loss: 0.3296
Epoch 42/100
4/4 ————— 0s 6ms/step - accuracy: 0.8159 - loss: 0.3298
Epoch 43/100
4/4 ————— 0s 6ms/step - accuracy: 0.8167 - loss: 0.3377
Epoch 44/100
4/4 ————— 0s 6ms/step - accuracy: 0.8128 - loss: 0.3394
Epoch 45/100
4/4 ————— 0s 6ms/step - accuracy: 0.8150 - loss: 0.3320
Epoch 46/100
4/4 ————— 0s 5ms/step - accuracy: 0.8195 - loss: 0.3298
Epoch 47/100
4/4 ————— 0s 6ms/step - accuracy: 0.8197 - loss: 0.3316
Epoch 48/100
4/4 ————— 0s 10ms/step - accuracy: 0.8198 - loss: 0.3297
Epoch 49/100
4/4 ————— 0s 6ms/step - accuracy: 0.8229 - loss: 0.3301
Epoch 50/100
4/4 ————— 0s 8ms/step - accuracy: 0.8190 - loss: 0.3281
Epoch 51/100
4/4 ————— 0s 6ms/step - accuracy: 0.8228 - loss: 0.3236
Epoch 52/100
4/4 ————— 0s 8ms/step - accuracy: 0.8155 - loss: 0.3301
Epoch 53/100
4/4 ————— 0s 6ms/step - accuracy: 0.8253 - loss: 0.3232
Epoch 54/100
4/4 ————— 0s 6ms/step - accuracy: 0.8276 - loss: 0.3268
Epoch 55/100
4/4 ————— 0s 8ms/step - accuracy: 0.8276 - loss: 0.3206
Epoch 56/100
4/4 ————— 0s 3ms/step - accuracy: 0.8263 - loss: 0.3241
Epoch 57/100
4/4 ————— 0s 6ms/step - accuracy: 0.8243 - loss: 0.3255
Epoch 58/100

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

4/4 ————— 0s 6ms/step - accuracy: 0.8271 - loss: 0.3240
Epoch 59/100
4/4 ————— 0s 6ms/step - accuracy: 0.8342 - loss: 0.3156
Epoch 60/100
4/4 ————— 0s 6ms/step - accuracy: 0.8315 - loss: 0.3184
Epoch 61/100
4/4 ————— 0s 4ms/step - accuracy: 0.8373 - loss: 0.3126
Epoch 62/100
4/4 ————— 0s 4ms/step - accuracy: 0.8377 - loss: 0.3122
Epoch 63/100
4/4 ————— 0s 4ms/step - accuracy: 0.8332 - loss: 0.3149
Epoch 64/100
4/4 ————— 0s 8ms/step - accuracy: 0.8317 - loss: 0.3154
Epoch 65/100
4/4 ————— 0s 4ms/step - accuracy: 0.8339 - loss: 0.3106
Epoch 66/100
4/4 ————— 0s 7ms/step - accuracy: 0.8331 - loss: 0.3100
Epoch 67/100
4/4 ————— 0s 6ms/step - accuracy: 0.8354 - loss: 0.3109
Epoch 68/100
4/4 ————— 0s 6ms/step - accuracy: 0.8368 - loss: 0.3105
Epoch 69/100
4/4 ————— 0s 4ms/step - accuracy: 0.8337 - loss: 0.3103
Epoch 70/100
4/4 ————— 0s 6ms/step - accuracy: 0.8460 - loss: 0.3027
Epoch 71/100
4/4 ————— 0s 6ms/step - accuracy: 0.8334 - loss: 0.3098
Epoch 72/100
4/4 ————— 0s 6ms/step - accuracy: 0.8413 - loss: 0.3037
Epoch 73/100
4/4 ————— 0s 4ms/step - accuracy: 0.8337 - loss: 0.3078
Epoch 74/100
4/4 ————— 0s 6ms/step - accuracy: 0.8378 - loss: 0.3093
Epoch 75/100
4/4 ————— 0s 6ms/step - accuracy: 0.8456 - loss: 0.3012
Epoch 76/100
4/4 ————— 0s 4ms/step - accuracy: 0.8437 - loss: 0.3024
Epoch 77/100
4/4 ————— 0s 5ms/step - accuracy: 0.8393 - loss: 0.3096
Epoch 78/100
4/4 ————— 0s 6ms/step - accuracy: 0.8477 - loss: 0.2972
Epoch 79/100
4/4 ————— 0s 6ms/step - accuracy: 0.8456 - loss: 0.3013
Epoch 80/100
4/4 ————— 0s 6ms/step - accuracy: 0.8436 - loss: 0.2958
Epoch 81/100
4/4 ————— 0s 6ms/step - accuracy: 0.8481 - loss: 0.2972
Epoch 82/100
4/4 ————— 0s 7ms/step - accuracy: 0.8494 - loss: 0.2983
Epoch 83/100
4/4 ————— 0s 7ms/step - accuracy: 0.8487 - loss: 0.2943
Epoch 84/100

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

```
4/4 ————— 0s 6ms/step - accuracy: 0.8550 - loss: 0.2878
Epoch 85/100
4/4 ————— 0s 6ms/step - accuracy: 0.8503 - loss: 0.2949
Epoch 86/100
4/4 ————— 0s 6ms/step - accuracy: 0.8520 - loss: 0.2905
Epoch 87/100
4/4 ————— 0s 6ms/step - accuracy: 0.8537 - loss: 0.2903
Epoch 88/100
4/4 ————— 0s 5ms/step - accuracy: 0.8512 - loss: 0.2934
Epoch 89/100
4/4 ————— 0s 6ms/step - accuracy: 0.8561 - loss: 0.2872
Epoch 90/100
4/4 ————— 0s 8ms/step - accuracy: 0.8560 - loss: 0.2884
Epoch 91/100
4/4 ————— 0s 6ms/step - accuracy: 0.8515 - loss: 0.2946
Epoch 92/100
4/4 ————— 0s 5ms/step - accuracy: 0.8576 - loss: 0.2909
Epoch 93/100
4/4 ————— 0s 7ms/step - accuracy: 0.8639 - loss: 0.2830
Epoch 94/100
4/4 ————— 0s 8ms/step - accuracy: 0.8612 - loss: 0.2843
Epoch 95/100
4/4 ————— 0s 8ms/step - accuracy: 0.8634 - loss: 0.2842
Epoch 96/100
4/4 ————— 0s 6ms/step - accuracy: 0.8628 - loss: 0.2778
Epoch 97/100
4/4 ————— 0s 4ms/step - accuracy: 0.8623 - loss: 0.2812
Epoch 98/100
4/4 ————— 0s 6ms/step - accuracy: 0.8643 - loss: 0.2813
Epoch 99/100
4/4 ————— 0s 6ms/step - accuracy: 0.8635 - loss: 0.2824
Epoch 100/100
4/4 ————— 0s 6ms/step - accuracy: 0.8692 - loss: 0.2789
125/125 ————— 0s 1ms/step - accuracy: 0.8686 - loss: 0.2801
Training Accuracy: 86%
----
----
500/500 ————— 0s 510us/step
Predicting the Droupout Test set results....
Dropout ANN confusion matrix:
[[2021 2073]
 [1925 9981]]
Test Accuracy: 75%
500/500 ————— 0s 643us/step
Predicting the stunting Test set results....
Stunting ANN confusion matrix:
[[6075 1980]
 [2040 5905]]
Test Accuracy: 74%
```

Appendix B PREDICTION RESULTS

IPython 8.30.0 -- An enhanced Interactive Python. Type '?' for help.

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

```
%runfile C:/AI/DSS-CHILD/predict.py --wdir
```

```
2025-06-30 10:07:11.411807: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
```

```
Setting the working directory.....
```

```
----  
----
```

```
Importing the libraries.....
```

```
2025-06-30 10:07:12.243552: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
```

```
2025-06-30 10:07:14.581067: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
```

```
To enable the following instructions: SSE3 SSE4.1 SSE4.2 AVX AVX2 AVX_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
```

```
----  
----
```

```
Importing the models.....
```

```
Importing the scalars.....
```

```
----  
----
```

```
Connecting to the database.....
```

```
Database URL: mysql+pymysql://root:***@localhost:3306/dss_child
```

```
Driver: pymysql
```

```
Dialect: mysql
```

```
Host: localhost
```

```
Port: 3306
```

```
Username: root
```

```
Database Name: dss_child
```

```
Connection successful.
```

```
----  
----
```

```
Insert the ID of the last child processed:19997
```

```
Data collected
```

```
----  
----
```

```
Data Preprocessing.....
```

```
Feature Scaling.....
```

```
----  
----
```

```
Predicting.....
```

```
1/1 _____ 0s 63ms/step
```

```
1/1 _____ 0s 24ms/step
```

```
----  
----
```

```
The results.....
```

```
The following are the predictions for child:
```

id	19998
Name	Savannah Garcia
age	13
Sex	Male
father_alive	0
mother_alive	1
parents_married	0
family_economic_status	good

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

```
is_vaccinated          0
number_of_meals_perday    3
is_working              1
type_of_work            Domestic work
years_working           2
number_of_siblings       12
parents_living_together  0
household_income_level   High
receiving_support        1
support_type             Uniforms
health_post             Kasempa Outreach Health
has_health_conditions     0
distance_to_healthpost    10.72
school                  Mtendere Primary School
attendance_rate           48.2
performance_level        Below Average
distance_to_school        13.32
has_dropped_out           1
stunted                  1
name                    Kasempa Outreach Health
has_antenatal_care        0
number_of_beds            1
number_of_staff           2
has_lab_services          0
has_pharmacy              0
ambulance_available       0
facility_level            Level 1
has_maternity_services    0
type_of_healthpost        Mobile
ownership                 Government
name                      Mtendere Primary School
number_of_classrooms      10
has_handwashing_facilities 1
has_electricity           1
has_water_supply          1
has_library               1
has_kitchen               1
has_feeding_program       1
number_of_pupils          530
number_of_teachers        19
school_shift              Single Shift
teacher_pupil_ratio       27.9
number_of_support_staff   4
Name: 0, dtype: object
----
```

The child is at risk of DROPPING OUT of school!
The child is at risk of becoming STUNTED!

The following are the predictions for child:

```
id          19999
Name        Nancy Lawson
age         7
Sex         Female
father_alive 0
```

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

```

mother_alive          1
parents_married       0
family_economic_status    Poor
is_vaccinated         0
number_of_meals_perday    3
is_working            0
type_of_work          None
years_working         0
number_of_siblings     12
parents_living_together  1
household_income_level  High
receiving_support      1
support_type          Fees
health_post           Chawama Community Health
has_health_conditions   0
distance_to_healthpost  1.83
school               Chelstone Basic School
attendance_rate        89.6
performance_level      Excellent
distance_to_school     10.23
has_dropped_out        0
stunted               0
name                 Chawama Community Health
has_antenatal_care     0
number_of_beds         4
number_of_staff        5
has_lab_services       0
has_pharmacy           1
ambulance_available    0
facility_level         Level 1
has_maternity_services  0
type_of_healthpost     Temporary
ownership             Government
name                 Chelstone Basic School
number_of_classrooms   13
has_handwashing_facilities  1
has_electricity        1
has_water_supply       1
has_library            1
has_kitchen            1
has_feeding_program    1
number_of_pupils       670
number_of_teachers     22
school_shift           Single Shift
teacher_pupil_ratio    30.5
number_of_support_staff  5
Name: 1, dtype: object

```

The child is NOT at risk of dropping out of school

The child is NOT at risk of becoming stunted

The following are the predictions for child:

```

id          20000
Name       Jaclyn Moore
age         9

```

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

```

Sex                                Male
father_alive                      1
mother_alive                      1
parents_married                   0
family_economic_status            good
is_vaccinated                     0
number_of_meals_perday             3
is_working                        0
type_of_work                      None
years_working                     0
number_of_siblings                12
parents_living_together           1
household_income_level            Low
receiving_support                 1
support_type                      None
health_post                      Solwezi Medical Centre
has_health_conditions              0
distance_to_healthpost            14.07
school                           Mumbwa Valley School
attendance_rate                   83.9
performance_level                 Good
distance_to_school                6.47
has_dropped_out                   1
stunted                          1
name                             Solwezi Medical Centre
has_antenatal_care                1
number_of_beds                    20
number_of_staff                   30
has_lab_services                  1
has_pharmacy                      1
ambulance_available               1
facility_level                    Level 3
has_maternity_services            1
type_of_healthpost                Permanent
ownership                         Private
name                             Mumbwa Valley School
number_of_classrooms              7
has_handwashing_facilities        0
has_electricity                   1
has_water_supply                  1
has_library                       0
has_kitchen                       1
has_feeding_program               1
number_of_pupils                  350
number_of_teachers                9
school_shift                      Single Shift
teacher_pupil_ratio               38.9
number_of_support_staff            2
Name: 2, dtype: object

```

The child is at risk of DROPPING OUT of school!

The child is at risk of becoming STUNTED!

Appendix C MODEL TRAINING CODE

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

```
#####
set working directory
#####

print('Setting the working directory.....')
import os
os.chdir('C:/AI/DSS-CHILD')
# remove warnings
import warnings
warnings.filterwarnings('ignore')
print("----")
print("----")
print("\n")

#####

Importing the libraries
#####

print('Importing the libraries.....')
import numpy as np
import pandas as pd
import tensorflow as tf
from sqlalchemy import create_engine
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, accuracy_score
import joblib
print("----")
print("----")
print("\n")
#####

Data Collection
#####

print('Connecting to the database.....')
# connect to the database
engine = create_engine("mysql+pymysql://root:@localhost:3306/dss_child")
print("Database URL:", engine.url)
print("Driver:", engine.dialect.driver)
print("Dialect:", engine.dialect.name)
print("Host:", engine.url.host)
print("Port:", engine.url.port)
print("Username:", engine.url.username)
print("Database Name:", engine.url.database)
print("Connection successful.")
# get data from the database
dataset = pd.read_sql("SELECT * FROM `child` c JOIN `healthpost` h ON c.health_post=h.name JOIN `school` s ON c.school=s.name ORDER BY c.id", engine)
# create the machine learning datasets
X = dataset.drop(columns=['id','Name','name','health_post','school','stunted','has_dropped_out'])
yd = dataset['stunted'].values
ys = dataset['has_dropped_out'].values
print("Data collected")
print("----")
print("----")
print("\n")
```

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

```
"""
Data Preprocessing
"""
print('Data Preprocessing.....')
# Encoding categorical data
le = LabelEncoder()
X.columns
loop = ['Sex', 'type_of_work', 'household_income_level', 'support_type', 'family_economic_status', 'performance_level',
'facility_level', 'type_of_healthpost', 'ownership', 'school_shift']
for item in loop:
    X[item] = le.fit_transform(X[item].values)
print("\n")

"""
Prepare the training and test datasets
"""
print('Splitting the dataset into the Training set and Test set.....')
# Splitting the dataset into the Training set and Test set
Xd_train, Xd_test, yd_train, yd_test = train_test_split(X, yd, test_size = 0.8, random_state = 0)
Xs_train, Xs_test, ys_train, ys_test = train_test_split(X, ys, test_size = 0.8, random_state = 0)
print("\n")
"""
Feature Scaling
"""
print('Feature Scaling.....')
# dropout datasets
scd = StandardScaler()
Xd_train = scd.fit_transform(Xd_train)
Xd_test = scd.transform(Xd_test)
# stunted datasets
scs = StandardScaler()
Xs_train = scs.fit_transform(Xs_train)
Xs_test = scs.transform(Xs_test)
# save the scalers
joblib.dump(scd, 'scd.pk')
joblib.dump(scs, 'scs.pk')

"""
Building the ANN
"""
print('Creating the Dropout ANN.....')
#### Create the dropout ANN
annd = tf.keras.models.Sequential()
# Add the hidden layers
annd.add(tf.keras.layers.Dense(units=43, activation='relu'))
annd.add(tf.keras.layers.Dense(units=21, activation='relu'))
annd.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))
print('Creating the Stunted ANN.....')
#### Create the stunted ANN
```

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

```
anns = tf.keras.models.Sequential()
# Add the hidden layers
anns.add(tf.keras.layers.Dense(units=43, activation='relu'))
anns.add(tf.keras.layers.Dense(units=21, activation='relu'))
anns.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))
print("Done")
print("----")
print("----")
print("\n")

"""
Training the ANN
"""

print("Training the Dropout ANN.....")
# Ensure that both X_train and y_train are NumPy arrays (or TensorFlow tensors) and are of compatible
Xd_train = Xd_train.astype('float32')
yd_train = yd_train.astype('float32')
# Compiling
annd.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
# Training the Dropout ANN on the Training set
annd.fit(Xd_train, yd_train, batch_size = 1000, epochs = 100)
loss, accuracy = annd.evaluate(Xd_train, yd_train)
print("Training Accuracy: "+str(int(accuracy*100))+"%")
print("----")
print("----")
print("\n")

print("Training the Stunted ANN.....")
# Ensure that both X_train and y_train are NumPy arrays (or TensorFlow tensors) and are of compatible
Xs_train = Xs_train.astype('float32')
ys_train = ys_train.astype('float32')
# Compiling
anns.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
# Training the Dropout ANN on the Training set
anns.fit(Xs_train, ys_train, batch_size = 1000, epochs = 100)
loss, accuracy = anns.evaluate(Xs_train, ys_train)
print("Training Accuracy: "+str(int(accuracy*100))+"%")
print("----")
print("----")
print("\n")
# save the models
annd.save('annd.keras')
anns.save('anns.keras')

"""
Predicting the Test set results
"""

yd_pred = annd.predict(Xd_test)
yd_pred = (yd_pred > 0.5).astype(int)
# Making the Confusion Matrix
yd_test = np.array(yd_test).astype(int)
cm = confusion_matrix(yd_test, yd_pred)
print("\n")
print("Predicting the Dropout Test set results....")
print("Dropout ANN confusion matrix:")
```

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

```
print(cm)
print("Test Accuracy: "+str(int((accuracy_score(yd_test, yd_pred))*100))+"%")
print("\n")
```

```
ys_pred = anns.predict(Xs_test)
ys_pred = (ys_pred > 0.5).astype(int)
# Making the Confusion Matrix
ys_test = np.array(ys_test).astype(int)
cm = confusion_matrix(ys_test, ys_pred)
print("\n")
print("Predicting the stunting Test set results....")
print("Stunting ANN confusion matrix:")
print(cm)
print("Test Accuracy: "+str(int((accuracy_score(ys_test, ys_pred))*100))+"%")
print("\n")
```

Appendix D PREDICTION CODE

```
"""
set working directory
"""
print('Setting the working directory.....')
import os
os.chdir('C:/AI/DSS-CHILD')
# remove warnings
import warnings
warnings.filterwarnings('ignore')
print("----")
print("----")
print("\n")
"""
Importing the libraries
"""
print('Importing the libraries.....')
import numpy as np
import pandas as pd
import tensorflow as tf
from sqlalchemy import create_engine
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, accuracy_score
from tensorflow.keras.models import load_model
import joblib
print("----")
print("----")
print("\n")
"""
Importing the models and scalers
"""
print('Importing the models.....')
annd = load_model('annd.keras')
anns = load_model('anns.keras')
print('Importing the scalers.....')
scd = joblib.load('scd.pk')
```

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

```
scs = joblib.load('scs.pk')
print("----")
print("----")
print("\n")
"""

Connect to the database
"""

print('Connecting to the database.....')
# connect to the database
engine = create_engine("mysql+pymysql://root:@localhost:3306/dss_child")
print("Database URL:", engine.url)
print("Driver:", engine.dialect.driver)
print("Dialect:", engine.dialect.name)
print("Host:", engine.url.host)
print("Port:", engine.url.port)
print("Username:", engine.url.username)
print("Database Name:", engine.url.database)
print("Connection successful.")
print("----")
print("----")
print("\n")
print("\n")
"""

Get children to be processed
"""

lastID = input('Insert the ID of the last child processed:')
# get data from the database
dataset = pd.read_sql("SELECT * FROM `child` c JOIN `healthpost` h ON c.health_post=h.name JOIN `school` s ON c.school=s.name WHERE c.id>"+lastID+" ORDER BY c.id", engine)
# create the machine learning datasets
X = dataset.drop(columns=['id','Name','name','health_post','school','stunted','has_dropped_out'])
yd = dataset['stunted'].values
ys = dataset['has_dropped_out'].values
print("Data collected")
print("----")
print("----")
print("\n")

"""

Data Preprocessing
"""

print('Data Preprocessing.....')
# Encoding categorical data
le = LabelEncoder()
X.columns
loop = ['Sex', 'type_of_work', 'household_income_level', 'support_type', 'family_economic_status', 'performance_level', 'facility_level', 'type_of_healthpost', 'ownership', 'school_shift']
for item in loop:
    X[item] = le.fit_transform(X[item].values)
print("\n")
"""

Feature Scaling
"""

print('Feature Scaling.....')
# dropout datasets
```

Enhanced Child Health & Social Protection through a Machine Learning Decision Support System

```
Xd = scd.fit_transform(X)
# stunted datasets
Xs = scs.fit_transform(X)
print("----")
print("----")
print("\n")
"""

Predicting the results
"""

# make the predictions
print('Predicting.....')
yd_pred = annd.predict(Xd)
yd_pred = (yd_pred > 0.5).astype(int)
ys_pred = anns.predict(Xs)
ys_pred = (ys_pred > 0.5).astype(int)
print("----")
print("----")
print("\n")
# print the prediction
print('The results.....')
i = 0
for index,row in dataset.iterrows():
    print('The following are the predictions for child:')
    print(row)
    print("----")
    if yd_pred[i][0]==1:
        print('The child is at risk of DROPPING OUT of school!')
    else:
        print('The child is NOT at risk of dropping out of school')
    if yd_pred[i][0]==1:
        print('The child is at risk of becoming STUNTED!')
    else:
        print('The child is NOT at risk of becoming stunted')
    print("\n")
    i = i+1
```