Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 27 May 2026
Revised 28 June 2026
Accepted 12 July 2026

Natural Resources for Human Health 2026, Vol. 6 (12s): 1277–1300

KEYWORDS:
Child malnutrition, Under-five children, Deep learning model, D-GRAM, Nutritional assessment, Public health programs, Tamil Nadu, Early detection

A Deep Gated Residual Auxiliary Multilayer Perceptron Model for Early Detection of Malnutrition in Under-Five Children in Rural Tamil Nadu

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ABSTRACT: Malnutrition among children remains a primary public health issue in India, with tangled demographic, socio-economic and clinical factors leading to malnutrition. The future generation is fundamentally dependent on the healthy childhood. The healthy child hood provides the foundation for cognitive development, emotional resilience and physical growth. Shaping these early phase of the life bring values, aspiration and capabilities in individual. It is one of the strategies to build more evolved, equitable and sustainable future. Tamil Nadu performs better than other states of India in nutritional programs for children under 5 years. The current programs like Uttachathai Uruthi Sei, breakfast schemes and RBSK screenings are showing nutrition security and community-based behavioural changes in Tamil Nadu. Still it is challenging to implement these programs in rural, tribal and urban poor areas. The two phases of screenings were conducted under the scheme of Rashtriya Bal Swasthya Karyakram (RBSK). The first phase (Apr – Sep 2024) reveals that 10.2% children are underweight, 3.3% are affected by Moderate Acute Malnutrition (MAM) and 1.9% children are suffered by Severe Acute Malnutrition (SAM). During the second phase (Oct – Mar 2025) 8% children are underweight, 3.8% are MAM and 2.5% are SAM. Though there is a marginal reduction in overall malnutrition from the first phase (15.4%) to the second phase (14.5%), the individual attention is needed to rectify this problem. The traditional screening techniques are relying on anthropometric measurements. The multi-dimensional analysis is required to solve an each individual child's malnutrition. This study presents the novel deep learning model - Deep Gated Residual Auxiliary MLP Model (D-GRAM) for early malnutrition detection in children under-five years. The multi-dimensional features dataset were collected from Anganwadi centres and mothers of the children from Thirumanur Union under the Ariyalur District, Tamil Nadu. This proposed model was developed with several optimization techniques and achieved 98% accuracy.

INTRODUCTION:

Malnutrition is one of most critical health issues in early childhood. It is contributing short-term and long-term impacts to the individual and society. Malnutrition is refers to the insufficient, excesses or disparities in the nutrition intake of the child during their early phase of the life (from birth to 5 years old). This is the foundational period for the physical development, brain development, cognitive functions and immune system functions. The less nutritional intake causes under-nutrition and excessive calories intake or regular intake of specific nutrients causes over-nutrition. But both are comes under malnutrition category with same kind of health crisis. [1] Malnutrition in toddlers producing long-lasting and irreversible consequences on their physical, emotional and cognitive developments. The impaired physical developments such as stunting (low height for age) and wasting (low weight for height) are the major causes of malnutrition. These are affects their height, weight and BMI which cannot be reversible if not treated early (before the age of 2). The cognitive developments are linked with the brain development. The delayed cognitive development affects the child with poor attention and learning difficulties. The micro-nutrients like iron, iodine and zinc are important for brain functions. Micro-nutrient deficiencies contribute in long-term difficulties such as memory, problem-solving, language learning and motor skills. These leads to lack of readiness to school and educational achievements. Additionally, malnutrition weakens the immune system. These lead the child to be vulnerable to infectious diseases like diarrhea, pneumonia, tuberculosis and measles.

As per the recent report of UNICEF–WHO–World Bank Joint Child Malnutrition Estimates-2023 [2], malnutrition in early childhood is one of the global health challenges.

- 148 million children under the age of five are affected by stunting, highlighting chronic under-nutrition.
- 45 million children are wasted, indicating acute malnutrition.
- 37 million children are affected by over-nutrition (over-weight or obese), representing the double burden of malnutrition.
- The first 1,000 days of one's life is the most critical phase for intervention.
- Nearly 50% of children deaths under 5 are associated to under-nutrition. Particularly, these deaths are happen in under-developed and developing countries.
- South-Asia alone consumes more than 50% of the stunted children of the world.

The National Family Health Survey (NFHS-5, 2019–21) report indicates several malnutrition statuses of the children under five in India. Though the economic development and various nutrition programs are implemented, India bears high burden of child malnutrition across globally.

Indicator	NFHS-4 (2015–16)	NFHS-5 (2019–21)	Trend
Stunting	38.4%	35.5%	↓ Decreased
Wasting	21.0%	19.3%	↓ Decreased slightly
Severe Wasting	7.5%	7.7%	↑ Slightly increased
Underweight	35.8%	32.1%	↓ Decreased
Overweight	~2.1%	~3.4%	↑ Increased

Table 1. Comparative Trend (NFHS-4 to NFHS-5) [3][4]

The above table (Table 1.) describes the comparative trend of NFHS-4 and NFHS-5. There is a slight improvement in stunting and wasting status of the children. The Severe Acute Malnutrition (SAM) status of the children has increased in many states. Overweight status of the children increased slightly while under-weight children are decreases in NFHS-5. [3] [4]

Due to the increased public private healthcare partnership in India, the advanced healthcare services utilization among women and children are quite lower than other developed countries. Even though Government led several interventions and investments in healthcare sectors, there is always a lag in child health indicators. The Integrated Child Development Services (ICDS) scheme incorporates with Anganwadi centres to achieve its objectives:

- Providing supplementary nutrition food for the children in the age group of 0 to 6 years and for the pregnant and nursing mothers.
- Non-formal pre-school education for the children in the age group of 3 to 5 years.
- Providing information related to every birth to the Panchayat secretary, or gram sabha sevak.

- Home visit to educate parents.
- Assisting PHC staff for the healthcare related works of this scheme like health check-up, immunisation, vaccinations etc.
- Assisting to organize the polio vaccinations drives.

Though Anganwadi centres addressing multi-dimensional issues related to healthcare, there is a persistent setback in rural areas regarding healthcare. [5] As per the information given by the Anganwadi Workers (AWWs), they are assigned to measure the weight and height of the children regularly to maintain the growth records of all children under the age of five. This process helps to identify the malnutrition as early as possible and implement timely intervention. The operational limitations weaken this system and its outcomes:

- The inconsistency in monitoring child growth measures due to lack of awareness in both parents and Anganwadi Workers.
- The Anganwadi Workers are responsible for multiple duties with limited time. This causes overburdened to Anganwadi Workers.
- Limited training and skills in Anganwadi Workers to detect the early warning signs of malnutrition.
- Manual-records are digitalized with some delays due to internet issues or lack of skills. It leads to errors in growth tracking systems.
- Children who are identified with malnutrition are not evaluated further due to communication gaps between Anganwadi centres and healthcare facilities. Some parents are not ready for the treatment due to their lifestyle and ignorance.

Combating malnutrition in toddlers needs early intervention, public involvement and integrated strategies focusing on healthcare, food supply and parental education. The early detection of malnutrition has challenges in real-time, especially in rural or tribal areas.

- Insufficient health care infrastructures: The rural healthcare centres are not well-equipped to monitor child growth or trained paediatrician. Lack of staffs in many Primary Health Centers (PHCs) and Anganwadi centers in rural or remote areas. Limited equipment access provides inaccurate measurements related to growth monitoring.
- Lack of skilled or trained workers: Due to the limited skills and training, the front line workers are not able to interpret the anthropometric features and identify the early warning signs of wasting, stunting and micronutrient deficiencies. The other common issues are inconsistent data collection and diagnostic errors.
- Weak surveillances and data management: The inconsistent digitalization of child records leads to poor documentation and missed follow-ups. Though the risk of malnutrition is persists, children often out of reach for regular monitoring.
- Lack of awareness: The caregivers and parents are often without awareness on malnutrition and its consequences leads to the illness to its severity. Cultural beliefs also one of the reasons to prevent the mothers and children to take necessary nutrients.
- Geographical or transportation challenges: Most of the remote villages are far from the healthcare units, without proper road access and transportation facilities. The routine screening may not be done in hill regions, tribal areas and underserved zones and leads to unaddressed or missed cases.
- Limited innovations and technologies: Though many of the mHealth tools (Poshan Tracker, growth apps, or SMS alerts) are adopted in real-time scenarios, poor internet connection and digital illiteracy remains challenging to address the early malnutrition.
- Gaps in nutritional schemes and policies: POSHAN Abhiyaan and ICDS schemes implementation are based on national-level statistics. The individual assessments are required to implement the targeted interventions. Children under 6 months and above 3 years are often fall outside of the focus. The inclusive policy interventions are required to detect early.

These barriers can be overcome by the use of AI-powered systems in early detection of malnutrition in children under 5 years old. The existing system analyses only the anthropometry values to detect the malnutrition status of the child. It is essential to include the environmental, clinical, social and economic factors to detect malnutrition. The high-dimensional data analysis will be helpful in detecting the risk factors associated with the child's malnutrition. The incorporation of deep learning model in early identification of malnutrition health status of the child provides the reliable and robust system in real-world applications. Deep learning is a subset of AI that delivers powerful tools in detecting complex patterns in huge and high-dimensional data.

- Predictive risk modelling: the deep learning model can able to integrate and analyse the complex datasets. The multi-dimensional features like clinical, socio-economical and anthropometric data can be included to predict the risk factors of malnutrition for the individual.
- Incomplete or noisy data handling: The collected data may be noisy or incomplete. The deep learning models facilitated with handling of incomplete data by imputation using auto encoders. It enhances the robustness and reliability of the model.
- Real-time decision support by Mobile devices: The DL-powered mobile applications provide instant and direct malnutrition status rather than providing individual risks.
- Incorporating IOT devices: Instead of manual measuring, integrating IOT devices with the equipments can provide the fastest and accurate measurements. It can work in areas without internet.
- Visualization of child growth: the deep learning model can provide overall growth chart of the child by analysing longitudinal growth measurements. This visualization helps in the early detection and forecasting future risks.
- Updating over time: The performance of the deep learning model can be updated based on the training of new or current dataset. It will provide accurate results based on the current trends.
- Data-driven outcomes: The results of the deep learning models are always data-driven. The data-driven decisions will provide the accurate predictive models.

The primary objective of this research is to developing a deep learning model to predict the malnutrition health status of the children under 5 years. This model will incorporates high-dimensional features - Identification features, Anthropometric features, Clinical Factors, Dietary and Nutritional behavioural factors, and Socio-Economic Factors to analyse the risk factors associated with the malnutrition status of the child.

LITERATURE REVIEW

Nutrition is a fundamental process that comprises nutrients which is used for growth, reproduction and managing the functions of human body. The proper nutrition helps to recover from the sickness and maintaining the health. The nutrition stages consist of ingestion, digestion, absorption, distribution, and exertion of the waste. In contrast, malnutrition causes serious issues to human body. It creates negative impacts to the life and raise of patients, increases morbidity, long hospital stay, mortality and health expenses. It happens due to poverty and diseases. Lack of food causes poverty which is primary malnutrition and secondary malnutrition caused due to various reasons accompanies with diseases:

- Reduced food intake
- Metabolic stress
- Consequences of multiple treatments

Early detection of malnutrition is important to implement required actions and to provide necessary nutritional support to reverse malnutrition. [6] Malnutrition occurs due to imbalanced nutrient intakes either insufficient or plenty of nutrient consumptions. It has two major forms: undernutrition and overnutrition. Both consists multiple subsets (Fig.1).

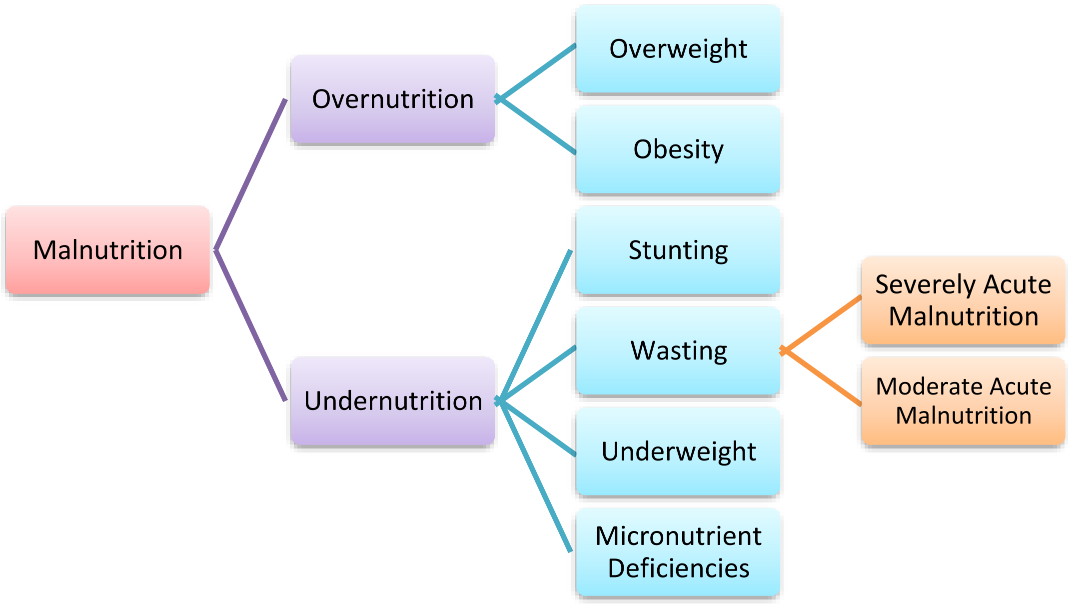

Fig. 1. Malnutrition Types [7] [8]

Three main indices of malnutrition are stunting, wasting and underweight. These conditions are referencing WHO growth charts to assess the status of these conditions.

- Stunting: The measure of height-for-age. The height of the child is compared with the children of the same age and gender. This condition can cause chronic malnutrition deficiency.
- Wasting: The measure of weight-for-height. The weight of the child is compared with its height by referencing the healthy children's anthropometric data. It can cause frequent illness like infectious diseases.
- Underweight: The measure of weigh-for-age. The weight of the child is compared with the children of the same age and gender. It causes severe weight loss. [8]

Malnutrition causes both short-term and long-term consequences in children. Some of the consequences are:

- The children of 2 years old consuming poor nutrients which lead to irreversible impact on their physical and cognitive growth. It is a chronic malnutrition.
- The malnourished children suffer from weakened immune system. It leads the children to be vulnerable to the diseases.
- The brain development would be affected and affecting their IQ, productivity and capability.
- The undernourished children suffer from recurring illness like infectious diseases diarrhea, pneumonia, measles and malaria etc.
- Micro nutrient like iodine and iron deficiencies with stunting restrict the children growth potential.
- The malnourished childhood leads to school dropouts, low cognitive skill and pregnancy related problems during their adulthood.
- Overweight or obese can cause metabolic and cardiovascular diseases.
- Malnutrition affects the reproductive potential later in their life.

The common reasons behind malnutrition are food insecurity, Government policies, socio-economic conditions, healthcare access and improper maternal and child care. [9] [10] The malnourishment affects the physiological functions of the human through diseases. Weight loss, respiration issues and other health related issues are the signs of malnutrition. Improper diet, digestive complications, alcoholism, mental health issues and mobility problems can have the potential to cause malnutrition.

The balanced diet with vegetables, fruits, grains and protein-enriched foods includes micronutrients which prevent malnutrition. The functional food helps for healthy life and it is essential to prevent the malnutrition. [11]

Malnutrition occurs due to improper nutrition, health and parenting practices. Inadequate amount of calories and nutrients intake, poor parenting behaviours, lack of maternal support, frequent illness contributed to the less absorption of nutrients and increase hungry. The other underlying factors triggering malnutrition are [9]:

- Inconsistent access to food, revenue and shelter are the crucial household insecurities contributing to malnutrition.
- Living condition and lower income affects their nutrition process.
- Water and sanitation are the major factors can cause infections.
- Access to healthcare is essential to managing childhood health.
- Frequent illness leads to risk of malnutrition.
- Basic infrastructure like transportations, roads and electricity can affect their access to food.
- Improper management of Government policies and political structure can cause inappropriate resource distribution.
- Cultural behaviours and traditions impacts parenting styles and limit diet distribution.
- Gender gap, social beliefs and education influence the diet routine.

Nutritional status of the child can be assessed by three ways. Anthropometric measurements - height, weight, head circumference and mid-upper arm circumference are used to detect the micronutrient malnutrition status associated with fats, proteins and carbohydrates of the children. The clinical symptoms – presence or absence of oedema and other clinical symptoms are used to determine the malnutrition status. The other method utilizes biochemical methods – finding haemoglobin level, blood ferritin level and retinol-binding protein level to confirm the particular micronutrient deficiencies. [8] This study evaluates the malnutrition status of children using gender, birth interval, mother's education, water resource and healthcare access through the survey and it was taken from rural areas of southwest Nigeria. [12] The study from Ethiopia uses random forest algorithm to detect the malnutrition status of children under five years by including parent's literacy rate, type of residence and rural-urban settlement as the determinants. [13]

Various Malnutrition Risk Screening (MNRS) tools are used to check the Paediatric Malnutrition (PMN). Still there is a gap in practicing and enhancements are needed. [14] The study found that Paediatric Yorkhill Malnutrition Score (PYMS) was better than the other paediatric malnutrition risk assessment tools. The results were compared with the WHO, Hellenic growth charts as well as with the local assessment practices. [15] Paediatric Yorkhill Malnutrition Score system expressed higher sensitivity for weight-for-age (90.9%) and BMI-for-age (84.6%) when compared with the Paediatric Nutrition Screening Tool (PNST). Still PNST produced better sensitivity for height-for-age as 88.9%. Both tools are efficient to detect the malnutrition risk of paediatric inpatients due to its high sensitivity. [16] In contrast, PYMS derived 100% sensitivity in acute malnutrition detection which is efficient for emergencies. STAMP was highly sensitive to detect chronic malnutrition and low Mid-Upper Arm Circumference SDs. These outcomes were compared with the Z-scores to determine the effectiveness of these tools. [17] The hospitalized children's malnutrition risks were detected using SPENS tool. It showed high sensitivity of 93.3% and specificity of 91.3% by utilizing four simple variables. It is fast and implemented in real-time for healthcare workers to detect malnutrition of the children and ensures early identification and intervention. [18]

Table: 2 - Existing Malnutrition Detection Models

Model	Type Of Data	Accuracy (%)	References
CNN With 0.001 Learning Rate	Image Data	96	[19]
Decision Tree	Survey Data	92	[20]
Random Forest	Open Source Data	91.11	[21]

CNN	Image Data	97	[22]
XGB Tree Algorithm	Survey Data	88	[23]
Efficient Net E7	Image Data	87	[24]
Lasso-XGBoost	Survey Data	72.8	[25]

Various malnutrition detection systems were implemented using machine learning and deep learning models. These models utilize image data or text data. The text data are taken from the survey or open source libraries. They have achieved significant accuracy in detection malnutrition status of the children. Still these results cannot be generalizable and applied for real-time practices. Many paediatric malnutrition screening tools are used in the healthcare sectors. Both of these tools and models are biased with the variables usage and related to different geographic regions. In India, multiple geographic regions, socio-economic groups and custom beliefs are followed by the people. These leads to nutritional changes in children under five years in different regions like remote areas, rural and tribal regions. These cases are remains same in Tamil Nadu also. As per the recent survey [26], 20.4 % children were affected by moderate malnutrition and 4.8% children were suffered by severe malnutrition. The anaemia affected children are 73.4% in Tamil Nadu. This unified survey masks the individual sufferings and leads to lack of targeted interventions for risk-prone children. The high-dimensional feature assessments and individual tracking system is required to eradicate malnutrition among the children under 5 years. The AI-driven techniques should be infused to detect the recent trends and personalization.

METHODOLOGY

PROBLEM STATEMENT

Malnutrition in toddlers and infants is the huge healthcare problems around the world, especially after COVID 19. The developing countries are the most affected regions due to its economic impacts, health sector strain and logistic and supply chain disruptions. The recent analysis in India says, out of 72.22 million children were measured and 96% of that children were assessed for the malnutrition status. 37% of children were affected by Severely/Moderately Stunted, 5% of the children were affected by Severe Acute Malnutrition/Moderate Acute Malnutrition, 16% were affected by Severely/Moderately Un derweight, and 6% of the children suffered by Obese/Overweight. [1] The comprehensive detection system on malnutrition prediction is required to identify the malnutrition status as early as possible. It is also important to include high-dimensional feature sets to identify the risk factors of the malnutrition status of the children. Though the deep learning networks are familiar in handling of image data, it provides more advanced analysis for high-dimensional text data. This study aims to build a comprehensive malnutrition prediction system using deep learning network. This prediction system detects the malnutrition status of the child under the age of 5 through high-dimensional features. This study includes step by step process: Data Collection, Target Variable Generation, Data Pre-Processing, Exploratory Data Analysis, Model Training, Testing, Model Evaluation and visualization and Hyperparameter Tuning.

DATA COLLECTION

The dataset collection process has been done with two-phase approach. These two-phase data consists of primary and secondary datasets and these two types of data were compiled to create a high-dimensional dataset.

1. Primary Data Collection: The primary data collection was conducted by visiting the Anganwadi centres around the Ariyalur district, Tamil Nadu, India. The door step survey was conducted around 120 Anganwadi centres, capturing identification and anthropometric features of the children under 5 years old. The data were collected based on the proper permission from the Child Development Project Officer (CDPO) of thirumanur union and with the help of Anganwadi Supervisor. Data were collected through direct visits to the villages, including Sannavur, Vilaagam, Kovil Yesanai, Venganur, Ilanthaikudam, and nearby villages of thirumanur union.

2. Secondary Data Collection: The secondary data were collected from the mother or guardian of the child through direct interviews. Every participant was informed about the concerns related to the data collection, data usage and confidentiality and

privacy over their personal and health data. The data were collected on a voluntary basis. These secondary dataset includes Clinical features, Dietary and Nutritional behaviours, and Socio-Economic features.

Both of these primary and secondary datasets were integrated using common attributes such as child's name, mother's name, father's name, gender, and DOB. This ensures the robust alignment and comprehensive analysis. This integrated approach improves the reliability of the dataset for estimating malnutrition health status.

DATASET DESCRIPTION:

The collected dataset consists of 19 attributes and 1154 records which can be organized into five groups of features – Identification features, Anthropometric features, Clinical Factors, Dietary and Nutritional behavioural factors, and Socio-Economic Factors.

1. The Identification features are utilized to uniquely identify the each record which comprises personal details of the child such as Child Name, Mother's Name, and Father's Name. It also includes child's Date of Birth (DOB) and Gender.
2. The anthropometric features are the main indicators to assess child's development and nutritional status. This data collection system comprises Height (in cm) and Weight (in kg) as the anthropometric attributes. It also includes born underweight (less than 2.5 kg at birth) feature to find whether the child was born underweight. It is a crucial metrics to analyse the malnutrition and growth variations.
3. The clinical factors can be used to analyse the recent health history and medical observation of the child. This factors captures the presence of any history of infections in the past three months (such as fever, cold, or diarrhea), whether the child has been diagnosed with any nutritional deficiency (like anemia or vitamin deficiency), the regular health check up status through growth monitoring at the Anganwadi centre, and the use of complementary supplements such as iron or multivitamins.
4. The dietary and nutritional features represent the eating habits and food sources of the child. It consists of and Nutritional Practices category reflects the child's eating habits and food sources. It includes the daily snacks and meals count, the diet type (e.g., consumption of staples, fruits, eggs, or junk food), whether the child consumes fruits or veggies daily, and if the child is an Anganwadi beneficiary receiving supplementary meals from the Anganwadi centre.
5. Socio-Economic features include the details of the family's living conditions and access to nutrition. The features capture the mothers education level, the monthly income of the household, and food accessibility, which indicates how easily fresh fruits and vegetables are available in the nearby area.

Table : 3 -Data Description

S.No.	Attribute Name	Description	Type	Possible Values / Format
1	Child Name	Full name of the child	Text	Alphabetic (e.g., "Ravi Kumar")
2	Mother's Name	Full name of the mother	Text	Alphabetic (e.g., "Sita")
3	Father's Name	Full name of the father	Text	Alphabetic (e.g., "Ram Kumar")
4	Born Underweight	Was the child born underweight (<2.5 kg)?	Categorical (Binary)	Yes, No
5	Snacks and Meals Count	Number of meals and snacks consumed by the child in a typical day	Numerical	Integer (e.g., 3, 4, 5)
6	Diet Type	Types of food the child regularly eats	Categorical (Multi)	Rice, Dal, Vegetables, Fruits, Milk, Eggs, Packaged/Junk Food (multi-select)

7	Fruits or Veggies Consumption	Does the child consume fruits or vegetables at least once a day?	Categorical (Binary)	Yes, No
8	Anganwadi Beneficiary	Does the child receive meals from Anganwadi center?	Categorical (Binary)	Yes, No
9	Complementary Supplements	Is the child regularly given dietary supplements (e.g., iron, multivitamins)?	Categorical (Binary)	Yes, No
10	History Of Infections	Has the child had illness in the past 3 months (fever, cold, diarrhea, etc.)	Categorical (Binary)	Yes, No
11	Regular Health Check Up	Is the child regularly monitored on a growth chart at Anganwadi center?	Categorical (Binary)	Yes, No
12	Any Nutritional Deficiency	Has the child ever been diagnosed with any nutritional deficiency?	Categorical (Binary)	Yes, No
13	Mothers Education Level	Education level of the mother	Categorical	No formal education, Primary, Secondary, Higher
14	Monthly Income	Monthly household income	Categorical (Ordinal)	Below ₹50000, ₹50000–₹100000, ₹100000–₹200000, Above ₹200000
15	Food Accessibility	Availability of fresh fruits and vegetables in local area	Categorical (Ordinal)	Very easily available, Moderately available, Limited availability, Not easily available
16	Dob	Date of birth of the child	Date	Format: YYYY-MM-DD
17	Gender	Gender of the child	Categorical (Binary)	Male, Female
18	Height	Current height of the child	Numerical (Continuous)	In centimetres (cm)
19	Weight	Current weight of the child	Numerical (Continuous)	In kilograms (kg)

TARGET VARIABLE GENERATION

The anthropometry values are used to determine the child nutrition status. The WHO undertaken the Multicentre Growth Reference Study (MGRS) between 1997 and 2003 which derive the new growth patterns to evaluate the development of infants and toddlers across the world. This study was performed on wide range of cultural backgrounds from India, Brazil, Oman, Ghana and the USA. [1] It offers the unique international standard for the growth assessment of the children from their birth to five years old. The DOB variable was parsed and ages were calculated in days using the formula given below:

$$day_i = latest\_date - DOB_i$$

Where, DOB_i is the Date of Birth of the i^{th} individual. Three attributes were created to assess the overall health of the child. They are stunting, wasting and weight status. These attributes were calculated using the growth chart of the World Health Organization (WHO) standards [34] and followed by the health care providers to examine the malnutrition health status of the children. Each parameter indicates the different dimension of the growth deficiency and nutritional deficiency.

● Stunting_Status: Stunting indicates chronic malnutrition. It is measured as the low Height-for-Age. This condition cause long-term insufficient nutrition and regular infections. These impacts on poor cognitive and physical ability which leads reduced productivity in their lifetime. The assessment chart for stunted classifies the stunting status with three types: Severely Stunted, Moderately Stunted and Normal. The stunted status can be assed based on the age (in days) and gender of the children.

● Wasting: Wasting indicates acute malnutrition. It is measured as the low Weight-for-Height. This condition cause severe weight loss as the result of intense food scarcity or illness. It leads to higher risk of mortality in young children. The assessment chart for wasted classifies the wasting status into five types: Moderate Acute Malnutrition (MAM), Severe Acute Malnutrition (SAM), Normal, Over-weight and Obese. The wasted status can be assed depending on the age (0-2 and 2-5), gender and height of the children.

● Weight_Status: The under-weight status indicates the under-nutrition in the children. It is measured as the low Weight-for-Age. This condition results from stunting, wasting, or both. It reflects both causes of chronic and acute malnutrition in young children. The assessment chart for under-weight status divided in to three types: Severely Underweight, Moderately Underweight and Normal. The underweight status can be identified with the age (in days) and gender of the children.

These three attributes defines the overall malnutrition health status of the infants and toddlers. The threshold-based classification method was applied to these attributes to derive the target variable – Nutritional_Health_Status. The objective of creating the unified target variable is to produce the direct and straight forward malnutrition health status of the children. The strong feedback on the child nutrition health status will be delivered through this model construction process. The health condition was segmented based on its risk level.

The risk levels identified as severe, moderate and normal. The severe problems include Severely Stunted from stunting attribute, Severely Underweight from underweight status attribute, Severe Acute Malnutrition and Obese from wasting attribute. The moderate problems include Moderately Stunted from stunting attribute, Moderately Underweight from underweight status attribute, Moderate Acute Malnutrition and Overweight from wasting attribute. The severe conditions secure more points, moderate conditions gain fewer points and normal condition stay without any points. The target variable - Nutritional_Health_Status secured four classes based on the total points.

1. Severe: The total is more than or equal to 5 resides in severe condition. It produces the highest impacts on the malnutrition health status.

2. Moderate: The total is between 3 and 4 moves to moderate condition. The significant impacts on the malnutrition can be detected in this condition.

3. Mild: The total is from 1 to 2 takes up to the mild condition. The small reflection on health issues can be identified with this condition.

4. Normal: Normal condition depicts no problem and it does not avail any points.

The creation of target variable based on threshold-based classification method merges the multiple malnutrition dimensions into a single label. The risk severity can be predicted more precisely on malnutrition health. It facilitates multi-class classification models for malnutrition prediction and ensures the data-driven consistency while predicting nutritional risk based on huge amount of datasets.

DATA PRE-PROCESSING

Pre-processing is one of the important step and it carrying out cleaning, integration, modification and restructuring of the raw data for further analysis and model building. It facilitates to reduce the bias probability. It will increase the data quality, usability and portability. [31] In this dataset, missing values, irrelevant attributes, cleaning, encoding processing was handled carefully to avoid bias and maintain efficient modelling.

- Handling missing values: The missing values cause incorrect feature importance, biased estimation, reduced accuracy and algorithm incompatibility. The collected dataset contains 49 records with missing values. These records have been removed to increase the data quality.

- Removing Irrelevant Attributes: Some of the attributes needs to be maintained with confidentiality and privacy according to the ethical guidelines of research. It should apply anonymity of participant's personal data in the research outcomes. This dataset holds irrelevant attributes such as Child Name, Mother's Name, and Father's Name. These attributes were removed to achieve the confidentiality of their personal data. Since the original target variable was formed, the stunting, wasting and underweight status attributes were removed to avoid data leakage and overfitting of the model.

- Cleaning and Standardization in Income Column: Most of the machine learning models cannot work with the special characters and strings. This dataset consumes Household Monthly Income attribute with special characters (₹, -, and ,). The special characters have been removed and the string values were converted into floating point representation.

$$HouseholdMonthlyIncome_i = float(regex\_extract(HouseholdMonthlyIncome_i))$$

- Label Encoding (Input Categorical Variables): The dataset comprises categorical variables which need to be transformed or encoded into numerical representation for training process. The input categorical variables such as born underweight, fruits or veggies consumption, anganwadi beneficiary, complementary supplements, history of infections, regular health check up, any nutritional deficiency, diet type, mothers education level, monthly income, food accessibility and Gender were encoded into integer codes.

$$X_i^{encoded} = LabelEncoder(X_i)$$

Where, X_i is the categorical features and $X_i^{encoded}$ holds the mapped integer codes.

- Target Variable Encoding: The encoded target variables are easy to store, transfer, train and test with the Deep Learning algorithms. The training and testing data should follow the same encoding method to maintain consistency. The target variable health status includes four categories – Normal, Mild, Moderate and Severe. The ordinal encoding was applied to this target values to transform it into the numerical form. The ordinal encoding provided 0 for Normal, 1 for Mild, 2 for Moderate and 3 for Severe classes.

$$Y_i = OrdinalCode(Nutritional\_Health\_Status_i\ )$$

Where, Y_i is the i^{th} encoded target attribute and $OrdinalCode(Nutritional\_Health\_Status\ _i)$ ordinal encoded function to i^{th} target values.

EXPLORATORY DATA ANALYSIS

The Exploratory Data Analysis (EDA) is a strategy and it is used for robust data exploration. It explores and visualizes the dataset to observe the crucial elements. The EDA process can be descriptive, statistical and graphical investigations. It will be done prior to the machine learning or statistical analysis. This mechanism helps to reveals the structure, distribution and relationships of the dataset. The important attributes, optimized data analysis techniques can be found in this process. Sometimes the anomalies were detected and removed to avoid the biased status. This EDA process is important in decision-making frameworks due to its efficient time saving mechanism. It restricts the mistakes arising from the hidden problems in dataset. [32] In this study, the EDA explores the visualization of feature correlation matrix and target variable distribution.

Feature Correlation Heat map: The correlation heat maps exhibits the correlation matrix with blue-to-white-to-red color gradient (Fig 1.). It illustrates the relationships between the features of the given dataset. Its correlation coefficient ranges from -1 to +1 which denotes the dependency levels and intensity of the relationships between the attributes. [33] The nutrition health status dataset has three levels of feature correlation with respect to the prediction of malnutrition of the toddlers. The anthropometric measures height and weight exhibits the strongest positive correlations with the nutrition health status as expected. The gender variations demonstrate the significant correlation with the target outcomes. Other factors like diet type, mother's education level, fruits/vegetables consumption, monthly income, and complementary supplements influence weak correlations with the outcomes.

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eISSN: 2583-1194

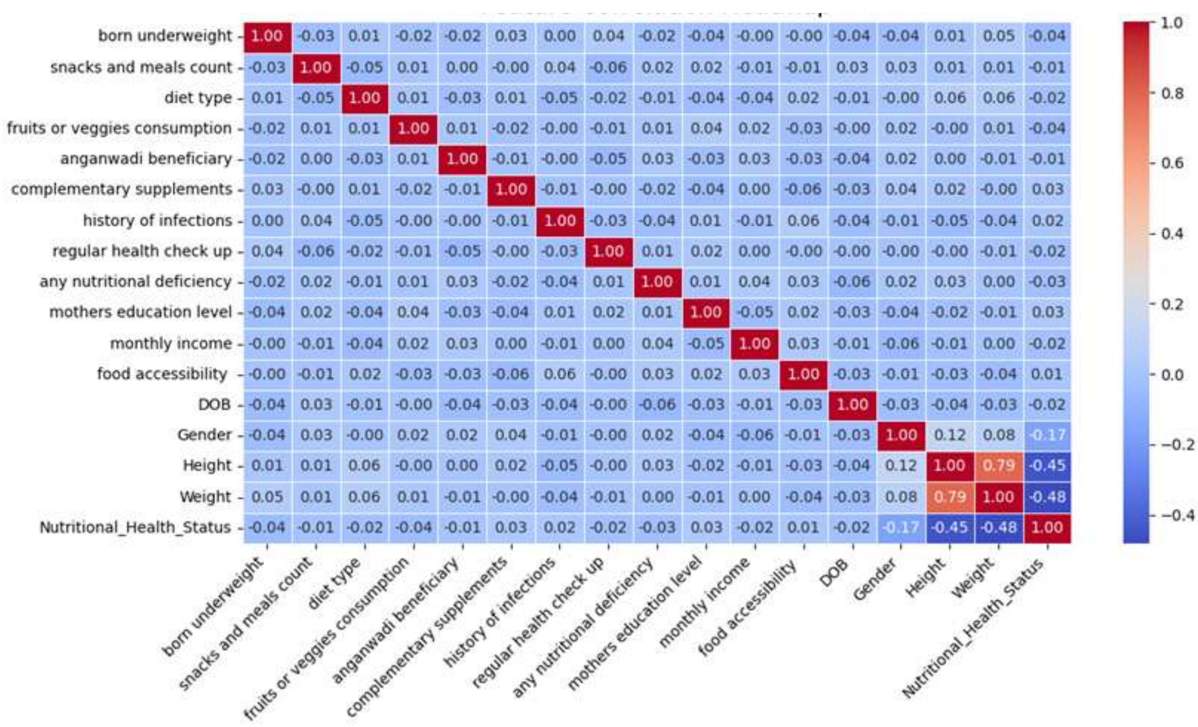

Fig 2. Feature Correlation Heat map

- Target Variable Distribution: The target variable values are distributed and show the imbalance among the target variable categories. The oversampling or synthesising of dataset is avoided to preserve the integrity of the dataset while addressing class imbalance issue. Tracking of F1-score can enhances the performance evaluation process of deep learning model.

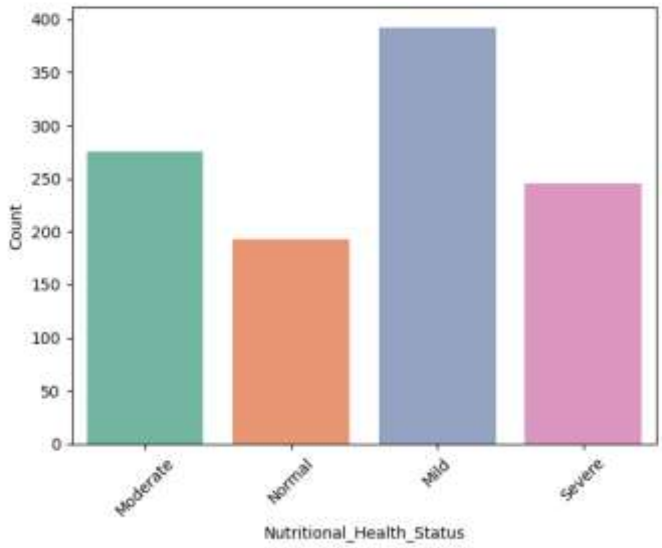

Fig 3: Target Variable Distribution

TRAIN – TEST SPLIT

The train-test split of data is an essential technique in machine learning model building to evaluate the effectiveness and robustness to the unseen data. It encompasses the process of dividing the dataset into two sets: training set and testing set. Training set is used to train the model and testing set will be used to evaluate the model performance. Test set is the unseen data (without output feature) while training set includes both input and output features. This split technique helps in the prevention of overfitting where generalization on new data fails. This step is an important step to verify the model's reliability and efficiency on current dataset but also with the real-time data. The dataset D, split into train-test with 80:20 ratios respectively.

$$D = D_{train} \cup D_{test}$$

PROPOSED DEEP LEARNING MODEL

The novel deep learning approach Deep Gated Residual Auxiliary MLP Model (D-GRAM) is a robust deep learning model designed to classify the malnutrition status of the child using the given input data. The embedding layers handle the categorical input data effectively. The core architecture of this proposed system includes:

- Embedding + MLP layers for representing the categorical features semantically.
- Gated MLP blocks controls the data flow over the network.
- Residual connections manage the gradient flow and supports deeper representation.
- Layer normalization and dropout technique enhances the training stability and regularization.

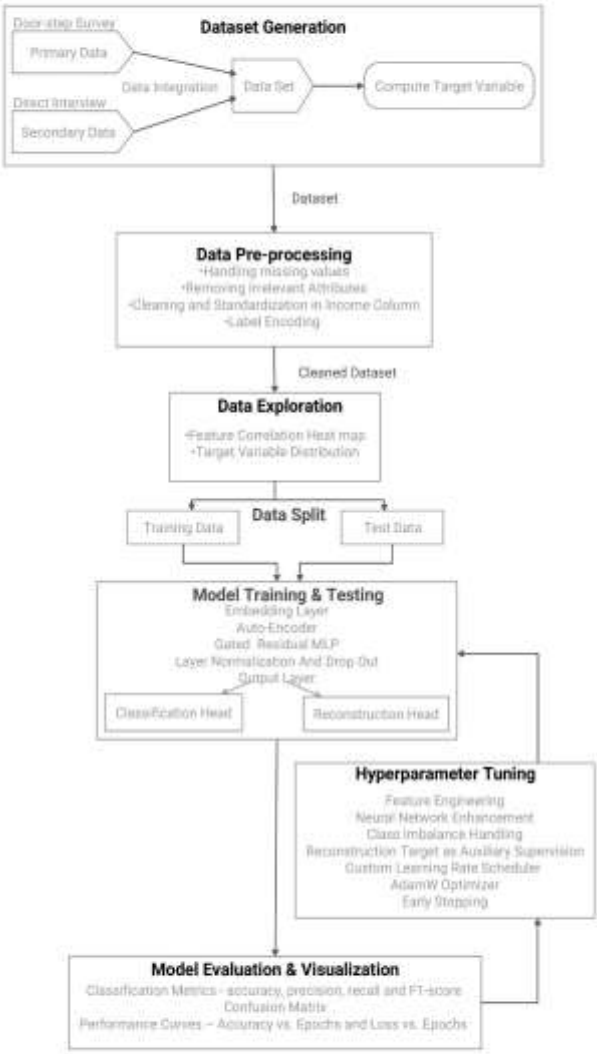

Fig 4: Proposed Model Architecture

The feature learning is improved by an auxiliary autoencoder which reconstruct the embedding inputs. The auxiliary loss promotes structural retention in the latent space, enhancing the generalization capability of the model. The two types of outputs are generated by this D-GRAM model: reconstructed embedding vectors for auxiliary supervision and the ultimate goal of the model - malnutrition status of the child.

Embedding layer construction: embedding layer is one of the type of neural network layers. It is used to represent the categorical variables as the dense vectors. The dense vectors consists of real numbers in a continuous vector space. Each categorical variables $\widehat{\boldsymbol{x}}_c \in \{0, \dots \dots, n\}$ are encoded into dense vectors, e_c.

$$e_c = W_c[\widehat{\boldsymbol{x}}_c], \quad W_c \in R^{n \times d}$$

Where $d = 4$, it represents the embedding dimension. These are flattened and concatenated to form a single vector. It becomes the input to the next layer of the deep learning model.

$$e = Concat(e_1, e_2, \dots \dots e_k)$$

Reconstruction Target Preparation: Reconstruction of target vector has been created for the autoencoder. The concatenation of embedding vectors $e_1, e_2, \dots \dots e_k$ and numeric features $x_1, x_2, \dots \dots x_k$ helps to learn meaningful patterns of the data.

$$x_{recon} = [e_1, e_2, \dots \dots e_k, x_1, x_2] \in R^{4k+2}$$

This reconstruction of target vector helps to train the model to output this full vector.

Gated Residual MLP: The Gated Residual MLP is a neural network utilizes gating approach which is a learnable filtering process to control the information flow. The residual connection is added to enhance learning stability and gradient flow. The training process is stabilized by applying layer normalization. It forms two parallel dense layers for feature transformation and gating signal. The feature transformation layer is a fully connected dense layer, h which transforms the input into more expressive.

$$h = ReLU(W_1 X + b_1)$$

the ReLU activation function is applied to pass only positive and zero values. This layer extracts the new and strong features from the input data. The another dense layer acts as a soft gate and applies Sigmoid activation function to retrieve the important parts of the transformed features. This gated output z is computed by multiply each element of h with the respective gate value in g:

$$z = h \odot g$$

This process provides the selectively activated representation, z.

Layer Normalization And Drop Out: This technique is applied to stabilize the learning process by subtracting the mean and dividing the standard deviation across the feature. Then the scaling and shifting process done with learnable parameters.

$$z_{norm} = LayerNorm(z)$$

The layer normalization normalizes neuron in every layer and randomly drops neurons during training to rectify the overfitting issue. These two techniques improve generalization and reduce the memorization risk. The residual connection is established to reuse the original input and to focus missing input in learning:

$$X_{out} = X + z_{norm}$$

Autoencoder Auxiliary Loss: This module try to reconstruct the input after encoding the input. It acts a regularizer and males the model to understand the structure of the input data. The true patterns over the data can be focused. It adds the reconstruction loss along with the main classification loss. The input of decoder is $h \in R^{32}$, latent vector which is a compressed version of original input. the decoder do the transformation using linear transformation:

$$\hat{x}_{recon} = W_{dec} h + b_{dec}$$

Where W_{dec} is weight matrix for the decoder with dimensions $(4k+2) \times 32$ and b_{dec} is bias vector with the size of $(4k+2)$. The output of autoencoder is $\hat{x}_{recon} \in R^{4k+2}$ which is a reconstructed version of the input and it matches the original input dimension.

Output layer: The final output layer constructed with dense layer and classification of nutrition health status of the child performed by leveraging the softmax activation function.

$$\hat{y} = \boldsymbol{softmax}\ (\boldsymbol{W_{class} X_{out}} + \boldsymbol{b_{class}})$$

Where $\boldsymbol{W_{class}}$ is weight matrix of the classification layer**, $\boldsymbol{X_{out}}$ is** output feature vector from the previous layer **and $\hat{\boldsymbol{y}}$** is the predicted probability distribution over classes.

In this proposed model, the classification loss, $\boldsymbol{L_{class}} = -\sum_{i=1}^{C} \boldsymbol{y_i log(\hat{y}_i)}$ and reconstruction loss (MSE), $\boldsymbol{L_{recon}} = \frac{1}{d}\sum_{j=1}^{d} \left(\boldsymbol{x_j} - \hat{\boldsymbol{x}}_j\right)^2$ are combined to calculate the overall loss:

$$L_{total} = L_{class} + 0.3\ .L_{recon}$$

The reconstruction loss is weighted by 0.3 which means this model gives more importance to the classification task still it pays attention to the reconstruction. This enables the proposed model to activate the multi-task learning setup and it is used to enhance the feature learning.

MODEL TRAINING AND TESTING

The training of Deep Gated Residual Auxiliary MLP Model (D-GRAM) was conducted around 100 epochs with early stopping and exponential learning decay. The hybrid loss function $\boldsymbol{L_{total}}$ is applied to address class imbalance and input reconstruction. The training data (80%) is applied to train the model and testing data (20%) is used to evaluate the performance of the model. the validation metrics guided the check-pointing.

HYPERPARAMETER TUNING AND OPTIMIZATIONS

Hyper parameter tuning enhances the performances of the model by finding optimal hyper parameters. It is crucial to detect the optimal parameters since it needs a systematic exploration of different parameters. In deep learning models, the hyper parameter tuning process minimizes the loss function while maximizing the accuracy of the model. The proposed deep learning model applied multiple strategies in hyper parameter tuning.

1. Feature Engineering: the new feature was derived to escalate the performance of the deep learning model. The BMI feature was created using the existing features Height and Weight.

$$\boldsymbol{BMI} = \boldsymbol{Weight}/(\boldsymbol{height})^2$$

The new attribute, $\boldsymbol{BMI}$ was standardized to efficient training of neural networks and embedded instead of one-hot encoding to less memory consumption and captures latent relations.

2. Neural Network Enhancement: The multi-task learning was applied to implement dual-output neural network architecture. The classification head classifies the child's nutritional health status (e.g., normal, moderate, severe and mild). The reconstruction head reconstruct the original input features from the latent representation. The more meaning internal features can be utilized during training. This reconstruction process regularizes the network, enhances generalization and reduces overfitting. The overall loss function was recalculated with tuned hyper parameters$\boldsymbol{\alpha}$ **and** $\boldsymbol{\beta}$, which balance these two tasks.

$$L_{total} = \boldsymbol{\alpha}.L_{class} + \beta\ .L_{recon}$$

3. Class Imbalance Handling: The class imbalance issue was addressed by computing class weights on class label distribution. These combined weights are used as custom loss function to flag misclassifications proportionally. Then the loss become $\boldsymbol{loss} * \boldsymbol{class\_weight}$ at the training process. These enable the training process to provide more attention to the underrepresented classes. Consequently, it increases the recall and overall performances on imbalanced classes.

4. **Reconstruction Target as Auxiliary Supervision: the concatenation of embeddings and numerical variables used as the reconstruction target. The semantic and structural information are retained in encoder through this**

auxiliary task. It is not only considers class distinctions but also ensures the detailed feature-level patterns in latent space. This supports the model to generalize better and improves stability and robustness during learning.

5. Custom Learning Rate Scheduler + AdamW Optimizer: the learning rate, η_t was reducing exponentially to for stable and gradual alignment.

$$\eta_t = \boldsymbol{\eta_0} \cdot \boldsymbol{\gamma}^{\lfloor \frac{t}{s} \rfloor}$$

Where, $\eta_0 = \mathbf{0.001}$, $\boldsymbol{\gamma} = \mathbf{0.9}$ and $\boldsymbol{s} = \mathbf{1000}$. It reduces overfitting at the later training stages. The AdamW optimizer integrates Adam with Weight decay to improve generalization. It decouples weight decay from gradient updates.

6. Early Stopping: The early stopping has been applied to by monitoring accuracy of the deep learning model. The training process halts after 10 stagnant epochs on validation accuracy decreases. The unnecessary epochs and training time were ignored. It ensures the optimal performance of the deep learning model on unseen or new data.

MODEL EVALUATION AND VISUALIZATION

The trained model was tested with 20% of the dataset which consists of only the input features. The evaluation metrics accuracy, precision, recall and F1-score were validated. The performance curves – Accuracy vs. Epochs and Loss vs. Epochs were plotted to visualize the performance of the proposed deep learning model.

RESULT AND DISCUSSIONS:

The study explores the early prediction of malnutrition among the children under 5 years using the novel deep learning model - Deep Gated Residual Auxiliary MLP Model (D-GRAM). This proposed system encompasses Multilayer Perceptron with various components: embedding layer, gates, residual connections, normalization, dropouts and auto encoder. The embedding layer converts the input data into dense vectors, the gates are used to control the flow if the data through the network, residual connection supports deeper presentation and maintain gradient flow, the normalization and dropout techniques have been used for stable training and regularization and auto encoder reconstructed the embedding inputs. The target variable consists of four categories: Severe, Normal, Moderate and Mild. The proposed deep learning model classifies the input data based on these four pre-defined outputs. The input data consists of identification, anthropometry, socio-economic, clinical and dietary information of the children. The classification metrics – precision, recall, F1-score and overall accuracy were computed to analyse the performance of this model. This model achieved 83% overall accuracy. Model's performance was visualized through confusion matrix (Fig. 1.), plotting accuracy over epoch (Fig. 3.) and loss over epochs (Fig. 4.). The bar chart was plotted to visualize the classification metrics values (precision, recall and F1-score) for each class labels in target variable (Fig. 2.).

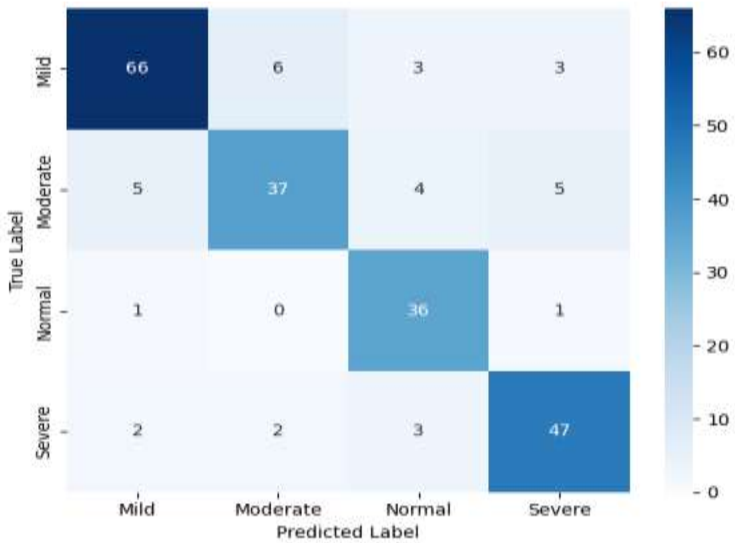

Fig 5: Confusion Matrix before Optimization

The confusion matrix (Fig. 1.) represents that the deep learning model performance for class label- Normal was better than the other three class labels. It predicted 36 class labels as normal out of 38 normal class labels. It represents lowest performance for the class label – Moderate. There are 14 class labels were misclassified and only 37 moderate classes were predicted into the moderate class. The bar chart (Fig. 2.) also represents the same kind of results.

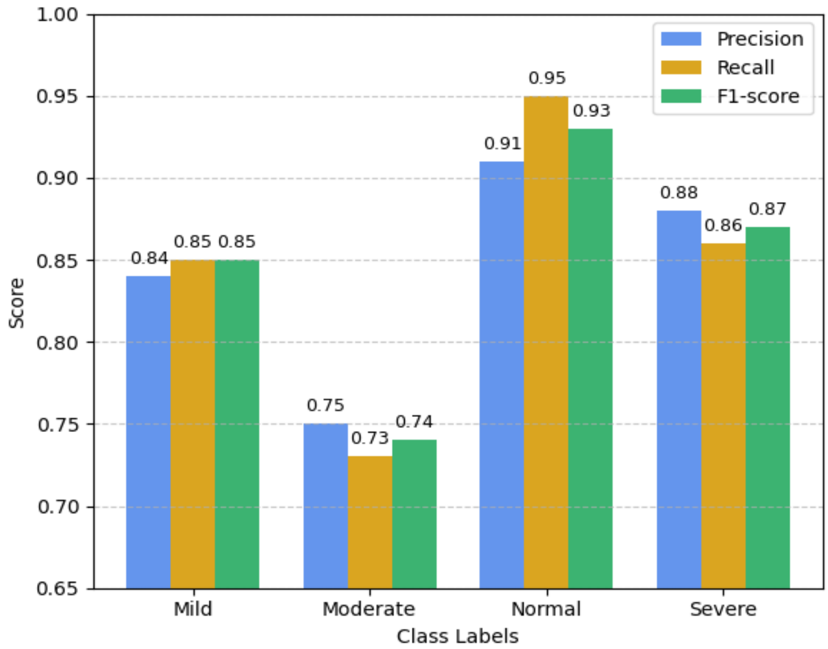

Fig 6: Classification Metrics for Each Class Labels

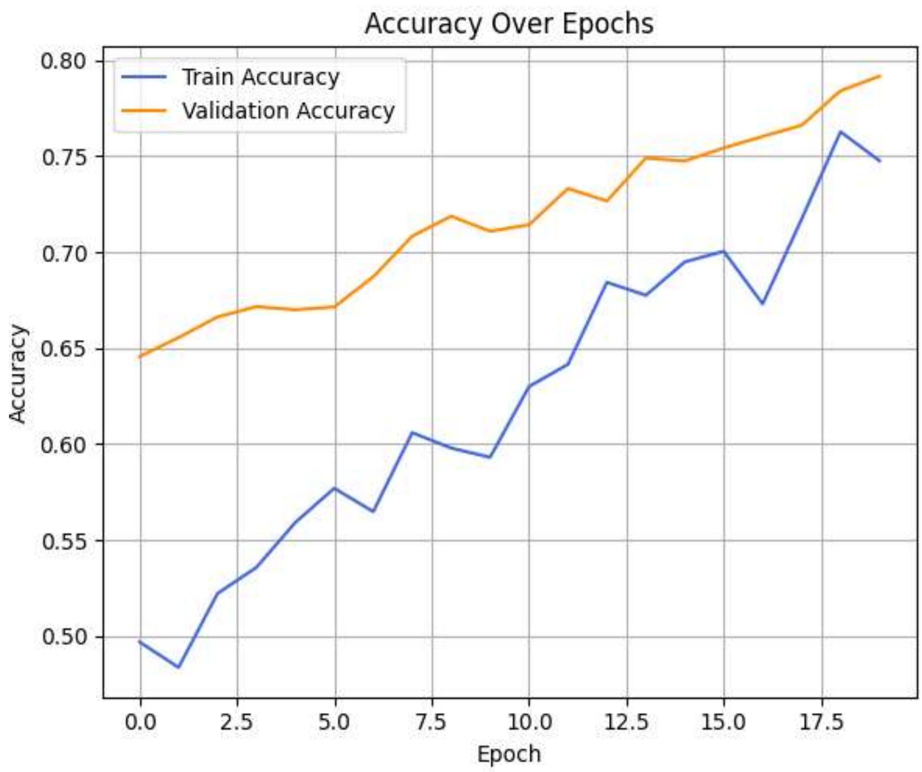

Fig 7: Accuracy over Epochs before Optimization

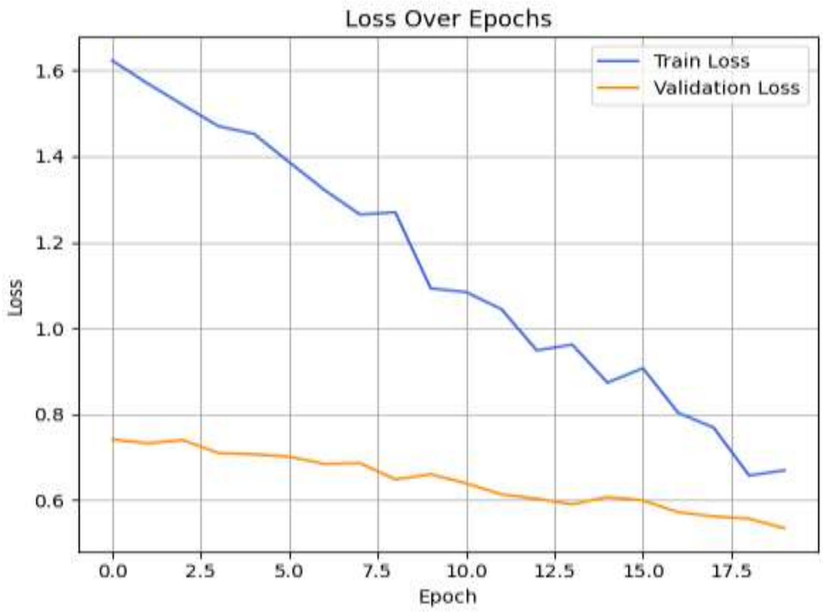

Fig 8: Loss over Epochs before Optimization

Table 4: Interpretation of Accuracy and Losses before Optimization

Metrics	Observation	Interpretation
Train Accuracy	Rising steadily (~0.48 → ~0.76)	Model is learning from training data
Validation Accuracy	Higher than train (~0.65 → ~0.79)	Possibly easier validation set
Train Loss	Steadily decreasing (~1.6 → ~0.65)	Model is fitting the data well
Validation Loss	Also decreasing (~0.75 → ~0.55)	No overfitting detected

The model was trained well since the training and validation losses were decreasing. The validation performance also improving along with the training which depicts no overfitting. But the unusual pattern was detected that the validation loss is better than the training. The optimization and hyper parameter tuning processes were implemented to enhance the performance of this proposed model.

The optimization process includes feature engineering, neural network enhancements, handling class imbalance, reconstruction target, custom learning rate, AdamW optimizer and early stopping. The new feature BMI was derived from the existing features to represents the rich and normalized data. Multi-task learning was applied for dual-output neural network which enhances the training process by understanding features. Class weights are leveraged to address class imbalance. The reconstruction target was created by concatenating numerical and categorical features. The faster and scalable convergence was acquired by the AdamW optimizer. Early stopping was initiated to ensure the optimal performance of the deep learning model. This optimized proposed system achieve 98% overall accuracy. The performance was visualized through confusion matrix (Fig. 5.), plotting accuracy over epoch (Fig. 7.) and loss over epochs (Fig. 8.). The bar chart was plotted to visualize the classification metrics values (precision, recall and F1-score) for each class labels in target variable (Fig. 6.).

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eISSN: 2583-1194

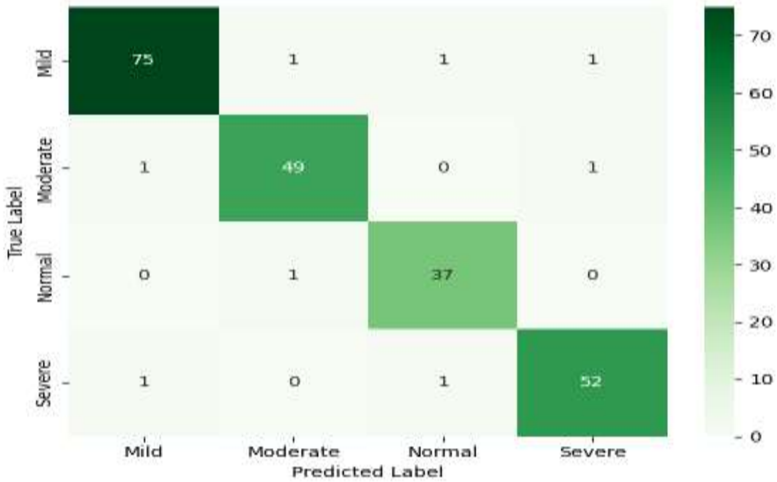

Fig 9: Confusion Matrix after Optimization

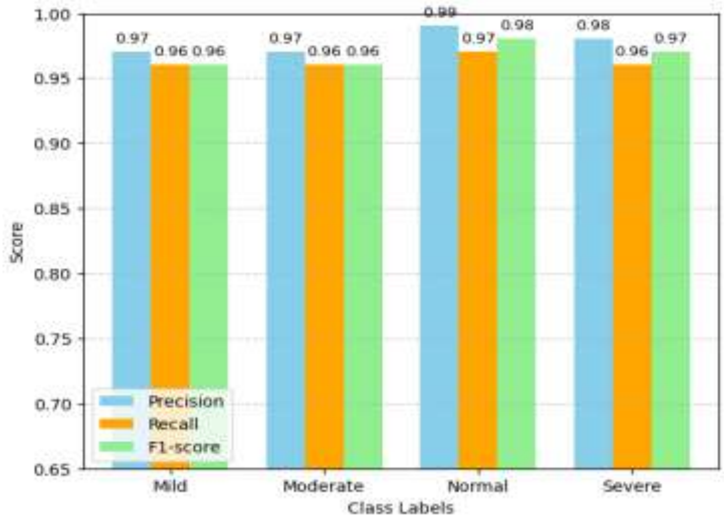

Fig 10: Classification Metrics for Each Class Labels after Optimization

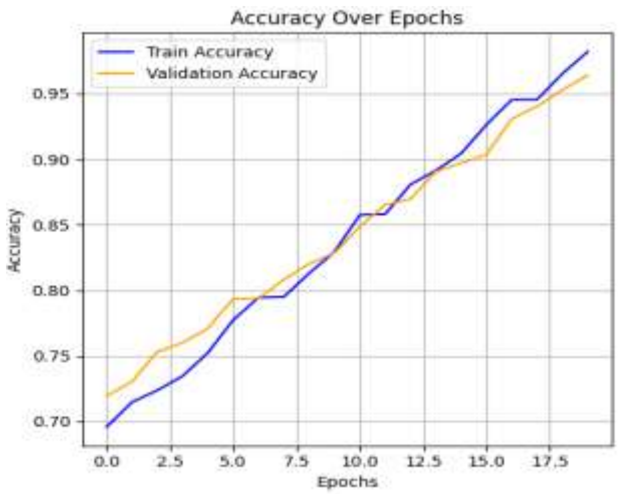

Fig 11: Accuracy over Epochs after Optimization

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eISSN: 2583-1194

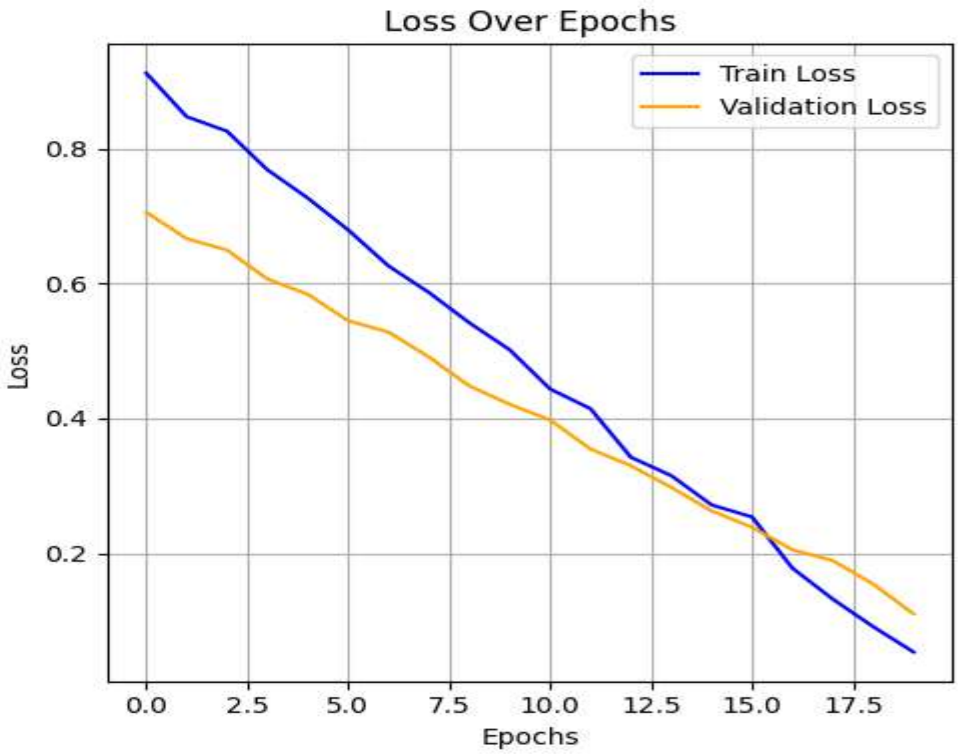

Fig 12: Loss over Epochs after Optimization

Metrics	Observation	Interpretation
Training Accuracy	Increased to ~0.98	Model fits training data very well
Validation Accuracy	Increased to ~0.96	Model generalizes well to unseen data
Training Loss	Decreased to ~0.05	Error on training samples is very low
Validation Loss	Decreased to ~0.12	Error on validation samples also very low

TABLE I. Interpretation of Accuracy and Losses after Optimization

The proposed model with optimization provides highest accuracy in both training and testing phases. Both training and validation losses were decreased considerably. There is no sign of overfitting or underfitting. The training and testing metrics were closely aligned which exhibits the well-tuned model with proper architecture and efficient regularization. The performance metrics of the Deep Gated Residual Auxiliary MLP Model (D-GRAM) before the optimization and after the optimization were represented in table (Table. III).

Table 5: Performance of the Deep Gated Residual Auxiliary MLP Model before and after Optimization

Performance Metrics	Class Labels	Before Optimization	After Optimization
Precision	Mild	0.84	0.97
	Moderate	0.75	0.97
	Normal	0.91	0.99
	Severe	0.88	0.98
Recall	Mild	0.85	0.96
	Moderate	0.73	0.96

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eISSN: 2583-1194

	Normal	0.95	0.97
F1-Score	Severe	0.86	0.96
	Mild	0.85	0.96
	Moderate	0.74	0.96
	Normal	0.93	0.98
	Severe	0.87	0.97
Macro Avg	Precision	0.84	0.98
	Recall	0.84	0.96
	F1-Score	0.84	0.97
Weighted Avg	Precision	0.83	0.98
	Recall	0.83	0.98
	F1-Score	0.83	0.98
Overall Accuracy		83%	**98%**

In the below image we demonstrate the target variable distribution. from the total data we collected we finally got the targeted output which is given below.

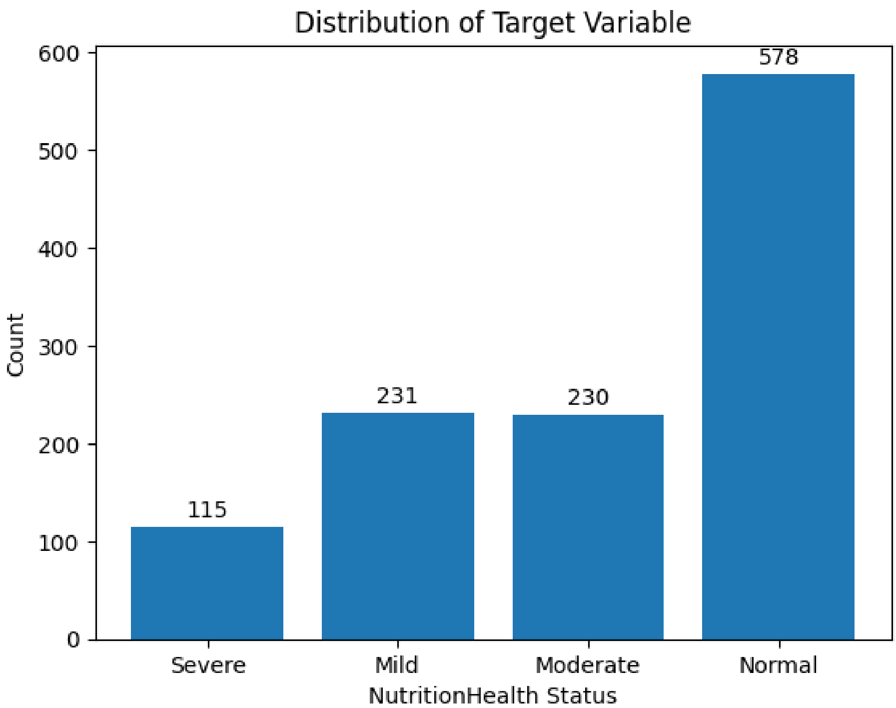

Fig:13 - Distribution of Target Variable

CONCLUSION:

This study addressed the critical health issue – malnutrition in children from Thirumanur Union under the Ariyalur District, Tamil Nadu by implemented and evaluated the novel deep learning model, Deep Gated Residual Auxiliary MLP Model (D-

GRAM). This model combines diverse and high-dimensional features such as identification, socio-economic, environmental, anthropometric and clinical features to detect the risk factors associated with the child's malnutrition. The anthropometric data were collected from the Anganwadi centres and remaining data were collected through structured interviews from the mothers of the children. The target variable – Nutrition Health Status was created by unifying the three malnutrition status of the child: Stunting, Wasting and Underweight. This deep learning framework was built with optimizations such as feature engineering, addressing class imbalance, neural network enhancements, **Reconstruction Target as Auxiliary Supervision**, custom learning rate, AdamW optimizer and early stopping. This model learned to classify children with one of the nutrition health status – namely Normal, Moderate, Mild and Severe. This helps to create awareness in public and make targeted interventions in affected areas.

Key Contributions

This research contributed to several benefits to both academics and child healthcare:

- Systematic Dataset Creation: The hybrid dataset with 16 features was created from both Anganwadi centres and mothers of the children under 5 years.
- Novel Deep Learning Framework: The study demonstrated the novel deep learning model with MLP for this child healthcare data.
- Real-time Application: This deep learning model has the potential to demonstrate in real-time and helpful for frontline healthcare professionals.
- Connecting innovation with child healthcare: This study fills the gap between the technology and child healthcare with this AI-powered system.
- Supports Targeted Interventions: This model helps the policy makers to identify the risk factors of the malnutrition status to make targeted interventions.

Limitations of the Study

The sample dataset was limited in both size and geographic ranges. It may affect the generalizability of the model's outcome. Though several pre-processing techniques were followed the data quality remains challenging. This model lies on cross-section study. The longitudinal data collection helps to acquire the deeper knowledge on malnutrition trends among the children.

Future Work

This research can be enhanced by collecting huge set of data in diverse geographical areas. The incorporation of temporal data may yield the correct patterns over the nutrition health status of the child. The IOT devices can be integrated to the instruments to prevent data inaccuracies instead of manual measurements.

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