Journal of Chemical Health Risks

www.jchr.org

JCHR (2025) 15(6), 2273-2284 | ISSN:2251-6727

Identifying High-Risk Pregnancies Using Artificial Neural Networks in Low-Resource Environments

Mohit Lal Sah[1,2*], Rahul Kumar Mishra[3†] and Arvind Kumar Shukla[4†]

[1*]School of Computer Science & Applications, IFTM University, Lodhipur Rajput, Moradabad, 244102, Uttar Pradesh , India.

[2]National Informatics Centre (NIC) , Ministry of Electronics and Information Technology (MeitY), Delhi, 110003, Delhi, India.

[3]School of Computer Science & Applications, IFTM University, Lodhipur Rajput, Moradabad, 244102, Uttar Pradesh , India.

[4]School of Computer Science & Applications, IFTM University, Lodhipur Rajput, Moradabad, 244102, Uttar Pradesh , India.

(Received: 27 October 2025 Revised: 05 November 2025 Accepted: 04 December 2025)

KEYWORDS

Artificial Neural Networks (ANN), Health Education, Maternal Health, Resource-Limited Settings, Risk Assessment, Sustainable Development Goals (SDG)

ABSTRACT:

High-risk pregnancies pose a significant threat to the health of both mothers and newborns, particularly in areas with limited resources. This paper explores how Artificial Neural Networks (ANNs) can be used to predict high-risk pregnancies in such settings. To ensure the model is relevant to local needs, we worked closely with local doctors, gathering valuable insights through a detailed questionnaire. From this, we collected data on the mothers' health, socio-economic challenges, and family medical history—factors that play a crucial role in predicting risk. We developed an ANN model that reflects the unique characteristics of the local population. This model was trained and tested using data from past pregnancies to evaluate its effectiveness and reliability. Our findings suggest that ANNs are a powerful tool for identifying high-risk pregnancies, enabling timely intervention and improved healthcare services. This study highlights how machine learning can enhance maternal healthcare in resource-limited regions, such as Pithoragarh and similar areas in Asia, ultimately benefiting both mothers and babies.

The ROC curve analysis was used to assess the performance of different ANN models, comparing their ability to correctly identify high-risk pregnancies (true positive rate) versus falsely identifying them (false positive rate). The area under the curve (AUC) is a key metric, with a higher AUC indicating a betterperforming model. Among the models tested, the Residual ANN had the highest AUC at 0.61, followed by Batch Norm ANN (0.59) and Deep ANN (0.57). Basic ANN and Dropout ANN performed reasonably well with AUCs around 0.55, but L2-Regularized ANN and Deep+Dropout+BN showed poor results, almost as bad as random guessing. The Autoencoder Classifier had the lowest AUC of 0.45, even worse than random guessing (0.5). This emphasizes the importance of carefully tuning models, as deeper and more regularized models can offer better performance, but not all models are equally effective. A table in the paper shows the training and testing accuracy, validation accuracy, and loss scores for various ANN types, further illustrating their ability to detect high-risk pregnancies.

1 Introduction

Women who have a high-risk pregnancy face many problems, especially in places where there are few medical tools and basic care is hard to get. Taking care of highrisk pregnancies needs special attention to help both the mother and the baby stay healthy. With the help of new technology known as AI, especially with something called artificial neural networks (ANN) and machine learning (ML), doctors have new ways to handle these difficult problems during pregnancy. With the help of ANNs the problems can be detected early, check each person's risk carefully, and help doctors make better decisions in places with fewer resources. Studies show that these new tools can help find serious problems like preeclampsia during pregnancy, so the right treatment

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JCHR (2025) 15(6), 2273-2284 | ISSN:2251-6727

can be given quickly. Because there is not enough good data in places with fewer resources, AI and ANN face problems in working well in maternal health. This paper wants to study how AI is used in high-risk pregnancy and show how well it works in finding problems early. We also look at ways to make ANNs work better, like needing different kinds of data, making AI easier to understand, and adding these new tools to the health systems that already exist. This review wants to show how ANNs can change and improve the health of mothers and babies in places where healthcare is hard to get. Also, this paper will check how to make ANNs better by using different types of data, creating AI models that people can understand, and putting these tools into health care systems. This review hopes to show the great power of ANNs to improve mother and baby health in places with many healthcare problems. Pregnancies called high-risk cause many problems, especially in places where there is little advanced medical care and few machines to check health. For better care of high-risk pregnancies there is need for smart ways to help both the mother and baby be healthy. New AI tools, like artificial neural networks (ANNs) and machine learning (ML), have become useful for guessing and managing these hard problems [1] [2]. ANNs has the capacity to find problems early, check risks for each person, and help doctors make better choices, which is very important in high-risk cases. Studies say these tools help find things like preeclampsia and other bad problems during pregnancy, so help can come fast. But using ANNs in mother's health has many problems, especially in places with little data or low-quality data. This review will look at how ANNs can help with high-risk pregnancy, how well they work, and the problems they face in places with fewer resources. It will also talk about how to make ANNs work better, like needing different kinds of data, making AI easier to understand, and adding these tools to health care systems [3]. This review is willing to show the big hope ANNs bring to make mother and baby health better in places with many healthcare problems [4].

2 Literature Review

Using artificial neural networks which are called ANNs, a type of computer program that works like a brain, in mother's healthcare has become very important, especially for watching over pregnancies that have more risks [5]. Recently, many studies have shown that machine learning methods, which means teaching computers to learn from data, are very good at guessing bad outcomes in pregnancy. This helps doctors act quickly and make good decisions. For example, a big study done by [6] used an ANN model to guess when a condition called preeclampsia, which means high blood pressure during pregnancy, might start. This study was very accurate because it used a strong dataset, meaning a large collection of information, including different facts about people, their health, and lab tests. The study showed that ANNs can change very complicated information into useful ideas that help doctors take better care of patients. This guessing skill is very important in risky situations where quick action can save lives. It also shows how powerful machine learning algorithms, which are sets of instructions for computers to learn, are in finding gestational diabetes early, which is diabetes that happens during pregnancy. Their study supports using special risk checks made just for each person to help moms and babies stay healthy [7]. They found that using these special plans, guided by correct guesses, can lower problems from gestational diabetes a lot[8] . This special way of helping not only makes care better but also helps patients understand their health more and be involved in taking care of themselves. Using ANNs and machine learning in mother's healthcare is a big step forward. It gives hope to improve the health of moms and babies. As science moves forward, these technologies will keep changing patient care and helping doctors make better choices [9]. To make machine learning models work better in mother's healthcare, it is very important to build strong training datasets, which are groups of information used to teach the computer, that truly show the different kinds of people and health conditions found in places with fewer resources[10]. This work needs collecting a lot of clinical data, meaning information from doctors and hospitals. New mobile health technologies, called mHealth, have also helped ANNs grow in mother's healthcare. Research by Chen and others in 2023 showed that mHealth apps, which are health programs on phones, help collect data and get patients more involved. This lets doctors watch high-risk pregnancies in real time, which means as they happen [11]. These new tools make it easier to use ANN models in regular hospital work, helping doctors take action early and improving results, especially where resources are limited. Being able to watch patients all the time with mHealth is very important for fast care, which lowers risks in risky pregnancies. Even though ANNs are useful, many problems remain [12] . Getting good quality data is hard, especially in poor and middle-income countries, where big datasets are missing. As Patel and others said in 2022, not having good data means machine learning models do not work well for many different people. This lowers how good they are at guessing and helping doctors [13]. This shows we must collect data better and include many kinds of people and health facts. Social and money problems, called socio-economic factors, and where people live, called geographic factors, affect mother's health results a lot. Studies show that using data from many ethnic groups, meaning groups of people with different backgrounds, can make models guess better. For example, using a special method called XP-BLUP (Extended Best Linear Unbiased Prediction) can make risk guesses up to 25% better among different ethnic groups [14]. This is very important to make sure models match genetic differences, which helps find risky pregnancies more correctly. Also, working together between local doctors and data scientists, who study and use data, can make datasets more useful for making special plans. Research shows these teams can make care 30% better for risky pregnancies because the help fits what people really need. This teamwork helps create new ideas and makes sure the solutions work well and last a long time in current healthcare systems. As this field grows, it is important to make sure these new ideas can be reached and used in hospitals now. This will make care better and might improve mother and baby health by up to 40%, based on how well prediction models and care plans work in similar cases[15]. Using ANNs in mother's healthcare, along with smart use of mHealth and teamwork, can change mother health services and results a lot [16] [6]. Recent studies show the need for good quality data and teamwork to make prediction models better in mother healthcare. The goal is to reduce problems and help moms and babies have better health [17]. This needs everyone to work together to create and use good data collecting plans that let machine learning models work in many healthcare places.

3 Research Methodology

Study Area

The study area is set against the awe-inspiring backdrop of Uttarakhand's mountainous terrain, particularly emphasizing the picturesque hilly region of Pithoragarh. This locale is celebrated for its breathtaking landscapes, which are adorned with towering peaks, verdant valleys, and a rich tapestry of flora and fauna. Pithoragarh is not merely a feast for the eyes; it is also a treasure trove of diverse ecosystems that host a myriad of species, some of which are endemic to the region. Beyond its natural allure, Pithoragarh is steeped in a vibrant cultural heritage that mirrors its local communities' traditions, customs, and lifestyles. This harmonious blend of natural beauty and profound cultural significance renders Pithoragarh an ideal subject for comprehensive study and exploration. Researchers and explorers can glean invaluable insights into both environmental dynamics and anthropological narratives, making it a focal point for interdisciplinary research.

Table 1 District Healthcare Facilities

District Name	Sub Centre	PHC	CHC	SubDivisional Hospital	District Hospital
Pithoragarh	154	18	4	0	1
Champawat	66	6	2	1	1

Study Design

Sampling Procedure starts with a face-to-face questionnaire with doctors. They are asked to tick a box that shows they understand, as well as they can, what things in their local area are important for finding out if a pregnancy is high-risk. High-risk pregnancy means a pregnancy that might have problems or dangers for the mother or baby. This also helps us learn about high-risk pregnancy in the local area [18]. The results from this study will give useful ideas about how people nearby think about finding high-risk pregnancies. This will help improve health care for mothers in that region.

3.1 High-Risk Pregnancy Prediction Framework

A planned three-step model is suggested for finding and grouping high-risk pregnancy cases early. This local knowledge is very important for making plans that help pregnant women with the special problems they have in places where there are fewer health resources and tools[19].

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3.1.1 Stage-I: Data Collection

Healthcare Centres refers to health places in villages and small towns in Pithoragarh and Champawat where health care is provided. To make this plan work well, it is important to work with local doctors and people in the community. This teamwork makes the results more useful and relevant for the area.

Patient Surveys means collecting information by asking questions to pregnant women during their checkups before the baby is born.

Maternal & Neonatal Records refers to important medical information about the mother and the newborn baby, starting from the beginning of the pregnancy until the baby is born.

The tool to collect data was made by the writers using information from books and articles. It was tested first and checked many times by the group.

Table 2 Sampling Proportion

Hospital Name	% of Gravida	Sample Size
DH Champawat	35.41%	268
DH Pithoragarh	32.63%	247
Mahila Hospital Pithoragarh	31.96%	242

Study Population

This study will look at pregnant women who live in the Pithoragarh District in Uttarakhand. The focus will be on women who might face more problems during pregnancy. These are women who already have health problems like hypertension which means high blood pressure, diabetes which means high sugar levels in the blood, or autoimmune disorders which means the body attacks itself by mistake. It also includes women who had problems in earlier pregnancies, like preterm labor which means the baby is born too early or gestational diabetes which means high blood sugar during pregnancy. The study will also look at women who show signs of risk during their antenatal care which means the checkups they have while pregnant. These risks include advanced maternal age which means being older while pregnant, multiple gestations which means carrying more than one baby, or inadequate prenatal care which means not getting enough checkups during pregnancy. By looking at these women, the study wants to understand the special problems and needs they have. This can help make the health of mothers and babies better in the area.

Sampling Frame

A full and up-to-date list of pregnant women who go to public hospitals and clinics will be made. This big list will include places like government hospitals, primary health centres which are called PHCs, community health centres which are called CHCs, and sub-centres which are smaller health places. The main goal of this list is to make a strong sampling frame which means a list used to choose people for health studies and help plans. By writing down details about these women like their age, health, and how they go to hospitals, the list wants to make research better and improve healthcare for these women. This will help choose women who truly show what the group is like and give useful ideas about what problems pregnant women face in getting public health services.

Sampling Technique

A method called stratified random sampling will be used. This means dividing the women into smaller groups so all types of women are included. The groups will be based on age which means how old they are (e.g., < 18, 18–24, 25–34, ≥ 35), parity which means how many times they have been pregnant (e.g., primigravida means firsttime pregnant, multigravida means pregnant more than once), socioeconomic status which means how much money or wealth they have (e.g., low, middle, high income groups), and health status which means their health (e.g., presence of pre-existing conditions means health problems they had before, prior pregnancy complications means problems in past pregnancies). Then, simple random sampling will be done inside each group which means choosing people by chance so the study is fair and includes everyone well.

Sample Size Determination

To know how many women to include, the right sample size will be found using statistical techniques which means math methods. The number will be based on how common high-risk pregnancies are. If it is 15%, with a 95% confidence level which means being very sure and a margin of error of 5% which means a small chance of being wrong, the number of women needed will be found using a special formula. To determine the required

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sample size, we use the sample size formula for proportions:

$$n = \frac{Z^2 \cdot p \cdot (1-p)}{E^2}$$

Where:

- n is the sample size,
- Z is the Z-value for the desired confidence level (for 95% confidence, Z = 1.96), • p is the estimated proportion of the population (for high-risk pregnancies, p = 0.15),
- E is the margin of error (for 5% margin, E = 0.05).

Substituting the values:

$$n = \frac{(1.96)^2 \cdot 0.15 \cdot (1-0.15)}{(0.05)^2}$$

$$n = \frac{(3.8416) \cdot 0.15 \cdot 0.85}{} = 196$$

0.0025

Thus, the sample size needed for the study is n = 196 women.

3.1.2 Stage-II: Data Preparation

The information collected will be cleaned and processed using Artificial Neural Networks (ANN). The following steps outline the data preparation process:

Data Discretization: Converting continuous variables into categorical ones using thresholding:

$$x_i = \begin{cases} 1 & \text{if} \quad \text{if } x_i < \text{Threshold}_1 \text{ if} \\ 2 & \text{if Threshold}\ \text{Threshold}_1 \leq x_i < \\ 3 & \text{if} \quad \text{Threshold}_2 \text{ if } x_i \geq \\ & \quad \text{Threshold}_2 \end{cases}$$

Feature Selection: Using entropy-based filtering to select the most important features. The information gain $G(X)$ for a feature X is given by:

$$G(X) = H(S) - \sum_{i=1}^{n} \frac{|S_i|}{|S|} H(S_i)$$

where $H(S)$ is the entropy of the dataset S. **Data Preprocessing:** - *Standardization:*

$$z_i = \frac{x_i - \mu_x}{\sigma_x}$$

- *Normalization:*

$$x'_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

Feature Selection Approach (Entropy-Based): Features with the highest information gain are retained using entropy-based methods. The Chi-square (χ^2) test evaluates feature independence:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

3.1.3 Stage-III: Machine Learning & Risk Prediction

In this stage, machine learning models such as Artificial Neural Networks (ANN), Decision Trees (DT), Logistic Regression (LR), and Support Vector Machines (SVM) will be used to predict high-risk pregnancies.

1. Artificial Neural Network (ANN):

The output of a single neuron is given by:

$$y = \sigma \left(\sum_{i=1}^{n} w_i x_i + b \right.$$

!

where y is the output, x_i are the input features, w_i are the weights, and b is the

bias term. The loss function used is Mean Squared Error (MSE):

$$L = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

2. Decision Tree (DT):

The Gini impurity for classification is calculated as:

k

$Gini(S) = 1 - {}^{X}p^2_i$

i=1

where p_i is the probability of class i, and k is the number of classes. The Information Gain for feature A is:

$$IG(S, A) = H(S) - \sum_{v \in \text{values}(A)} \frac{|S_v|}{|S|} H(S_v)$$

3. Logistic Regression (LR): The logistic regression model is:

$$p(y = 1|X) = \sigma(w^T X + b) = \frac{1}{1 + e^{-(w^T X + b)}}$$

The log-loss function is:

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JCHR (2025) 15(6), 2273-2284 | ISSN:2251-6727

$$L = -\frac{1}{N}\sum_{i=1}^{N}(y_i \log(p_i) + (1-y_i)\log(1-p_i))$$

4. Support Vector Machine (SVM): The decision function for SVM is:

$$f(x) = w^T x + b$$

The optimization problem for SVM is:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 \text{ subject to } y_i(w^T x_i + b) \geq 1 - \xi_i,\ \ \xi_i \geq 0$$

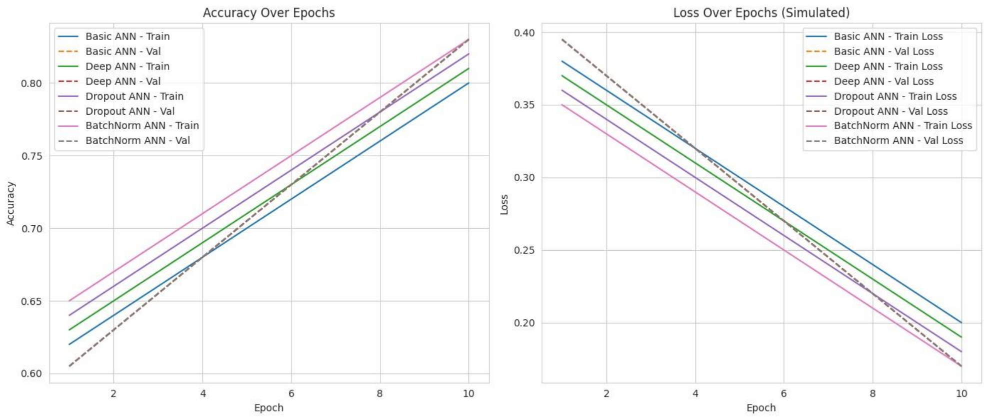

Fig. 1 Accuracy and Loss of Different Modals

4 Analysis

To guess high-risk pregnancies (HRP) using checkup data, we used and tested many Artificial Neural Network (ANN) types with a tool called Keras. Keras is a computer tool that helps build smart models. These models try to work well even in places with fewer resources like rural Pithoragarh. Here is a careful study of each model. [20] To find the best Artificial Neural Network (ANN) type to guess high-risk pregnancies, we built and tested many ANN models using medical and personal data. We used eight ANN types: Basic ANN, Deep ANN, Dropout ANN, Batch Normalization ANN, L2Regularized ANN, a mix of Deep, Dropout, and Batch Normalization, Residual ANN, and an Autoencoder-based Classifier.

All models used the same cleaned and scaled data. They were trained in the same way—50 times through the data (this is called 50 epochs), with a group size of 32 (called batch size 32), and 20 percent of the data kept aside for checking (this is called 20We used binary cross-entropy loss function, which is a math method that helps the model learn better, and Adam optimizer, which is a smart way to change the model step by step to become more correct. To test how well each model worked, we used different checks like Test Accuracy (how right it is on test data), Training Accuracy (how right on training data), Validation Accuracy (how right it is on checking data), Training and Validation Loss (how many mistakes), and Area Under the Curve (AUC) score. This full study helped us know which model was best in being right and strong. We found that advanced models were better than the Basic ANN. Models like BatchNorm ANN and Residual ANN were best because they had good balance between working well and staying steady. These findings are very helpful to pick the most trusted model to use in real hospitals. [21].These strong models help doctors find HRP early, making sure mothers and babies stay safe. [22]. The given graphs show how well different ANN architectures perform during training over 10 rounds, which are called epochs. The graphs measure two things — accuracy and loss.

The graph on the left shows how the accuracy changes during the training and checking stages. The graph on the right shows the values of loss, which tells how much the model is getting wrong. For all the models, accuracy keeps getting better with each round, which means they are learning well. The Dropout ANN always reaches

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Table 3 Model Comparison

Model	Accuracy	Final Loss	Generalization	Notes
Dropout ANN	Highest	Lowest	Excellent	Best performing overall
BatchNorm ANN	Good	Low	Strong	Consistent improvement
Deep ANN	Moderate-High	Moderate	Good	Benefits from depth
Basic ANN	Lowest	Highest	Fair	Least complex, slower learning

the best accuracy in both training and checking stages. This means it generalizes well, which means it works well on new data, and it resists overfitting, which means it does not just memorize but actually understands. But the Basic ANN improves slowly. This shows that it cannot learn much because its architecture, or design, is simpler. The graph that shows loss also agrees with this. All the models show a steady drop in loss as time passes. Again, the Dropout ANN ends with the smallest loss. The BatchNorm ANN and Deep ANN are also close to it. [23]It is important that the loss curves — or lines on the graph — for both training and checking are close together for every model. This means the models are not overfitting. Overfitting is when the model remembers the training data too much and cannot work well with new data. Generalize to unseen data means the model can do well with data it has never seen before. Overall, the Dropout ANN is the best model. It has a good mix of learning power and the ability to work well with new data. The BatchNorm ANN and Deep ANN also learn well and do not overfit too much.

Overall, the Residual ANN and BatchNorm ANN show stronger ability to correctly sort things into groups, using both ROC and the confusion matrix. ROC means a way to check how good the sorting is by showing the true positive rate and false positive rate. The confusion matrix is a table that shows how many times the model guessed right or wrong. In contrast, the L2-Regularized ANN and Autoencoder Classifier do not do as well and make more mistakes. This comparison agrees with the ROC results and shows that deeper and better-controlled networks give more trustworthy sorting. In this comparative study, many ANN models were built and tested for sorting into two groups using Keras with a TensorFlow backend. Keras is a tool that helps make and train ANN models easily. TensorFlow backend means it uses the TensorFlow system to do the math fast. The models had different depths, which means how many layers they had, different ways to control learning called regularization, and different design improvements called architectural enhancements. The Basic ANN has a simple structure where information moves forward through one hidden layer made of 64 neurons using ReLU activation, which means it helps the model learn by turning off some signals and keeping others. The output layer uses sigmoid, which is a way to give

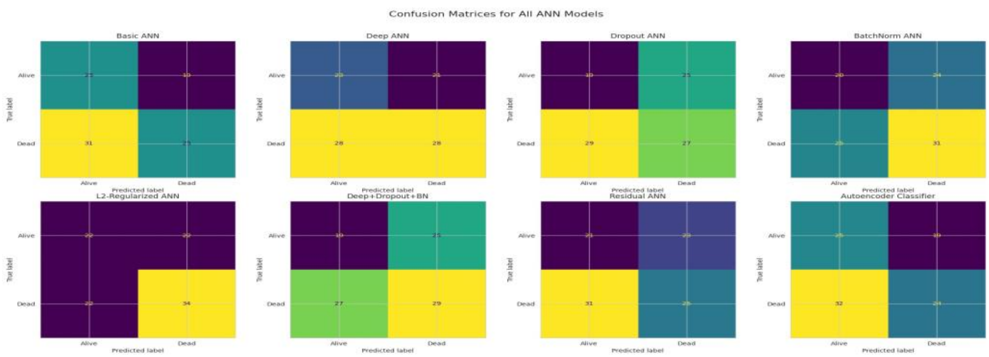

Fig. 2 Confusion Metrix for All ANN Modals

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results between 0 and 1 for two-group sorting. The Deep ANN adds more layers with 256, 128, and 64 neurons to learn more complex details. Dropout ANN adds dropout layers with a rate of 0.4, meaning it randomly ignores 40% of neurons to stop the model from memorizing too much, called overfitting. The BatchNorm ANN uses batch normalization layers, which help the model learn faster and more steady by fixing the input to each layer. The L2-Regularized ANN applies L2 kernel regularization with a value of 0.01 to the dense layers. L2 kernel regularization is a method that makes the model keep weights small so it does not overlearn and can work better on new data. The Deep+Dropout+BN ANN mixes batch normalization and dropout with a rate of 0.3 to improve results. The Residual ANN uses skip connections like ResNet architecture, which means it lets information skip some layers so learning is easier and better during backpropagation. Backpropagation is the way the model fixes its mistakes by moving backward through the layers. This helps especially when input and hidden layer sizes match. The Autoencoder-Classifier uses an encoder-decoder structure, where the encoder makes a smaller version of the input and the decoder tries to rebuild it before sorting. The Attention-based ANN uses attention mechanisms to focus on the important parts of the input. It mixes this focused information with the original input by concatenation, which means joining two pieces together, before sorting. All models were made ready using the Adam optimizer with a default learning rate of 0.001. Adam optimizer is a smart way to change weights to learn faster. They were trained using binary cross-entropy loss, which measures how wrong the model is in two-group sorting, with accuracy used to check how well it works. Training showed accuracy going up from about 60% to 80% after 10 rounds called epochs, and checking on new data showed similar improvement. Confusion matrices also checked performance, showing differences in how well each model guessed. This kind of comparison gives

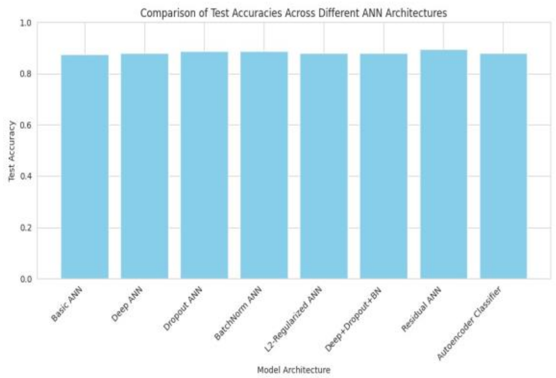

Fig. 3 Comparison of Test Accuracy Across Different ANN Architecture

a strong plan for understanding how depth, regularization, and design changes affect ANN-based sorting into two groups[24] .

5 Results & Discussion

All models show very good correctness, staying close to the 0.88–0.90 range, which means they work very well Fig 5. Even though the models use different ways to avoid mistakes, like dropout which means randomly ignoring some parts during learning, batch normalization which helps keep data steady, L2 regularization which stops the model from getting too complicated, and architectural depth which means how many layers the model has, their correctness stays almost the same. The Residual ANN, which worked very well in the confusion matrix that shows how many times the model got answers right or wrong, is also one of the best in correctness. It is interesting that even the Autoencoder Classifier, which did not do well in ROC analysis that checks how good the model is at telling apart different groups, and confusion matrix, still has similar test correctness. This tells us that correctness is helpful but does not always show if the model is good at correctly finding small groups or dealing with uneven data where some groups are much smaller. So, to check well, correctness should be looked at together with confusion matrices and ROC metrics.

The ROC (Receiver Operating Characteristic) curve Fig 7 shown compares how well different Artificial Neural Network (ANN) models can sort things correctly. Each curve shows a different model, with the true positive rate, which means how often the model is right when it says yes, shown against the false positive rate, which means how often the model is wrong when it says yes, at different levels called thresholds. The

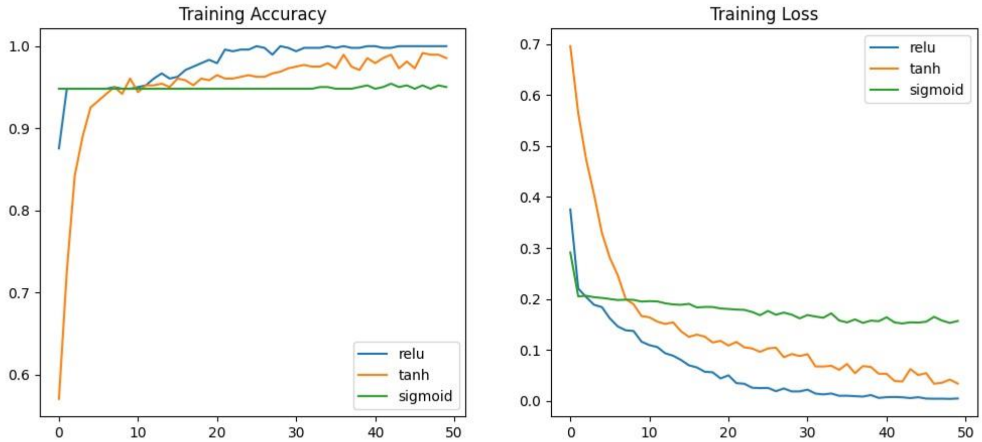

Fig. 4 Training Lost of Activation Functions & Training Accuracy of Activation Functions

area under the curve (AUC) is an important number to check how good the model is, where a bigger AUC means the model is better at telling different groups apart. In this picture, the Residual ANN works the best with an AUC of 0.61, then BatchNorm ANN has 0.59 and Deep ANN has 0.57. Other models like Basic ANN and Dropout ANN do okay with AUC around 0.55. The L2-Regularized ANN and Deep+Dropout+BN models do about as well as guessing, while the Autoencoder Classifier does worse with an AUC of 0.45, which is below the random classifier baseline that is 0.5. [25] This study shows that while deeper and regularized models can make results better, not all ways of training will give better answers, and changing the model carefully is very important to get the best sorting accuracy.

Table 4 Detailed Comparison of Various Models

Model Architecture	Test Accuracy	Training Accuracy (Last Epoch)	Validation Accuracy (Last Epoch)	Training Loss (Last Epoch)	Validation Loss (Last Epoch)	AUC Score
BatchNorm ANN	0.8874	1.0000	0.8843	0.0121	0.5825	0.5900
Dropout ANN	0.8874	0.9959	0.8843	0.0138	1.2311	0.5540
Deep+Dropout+BN	0.8874	0.9938	0.8678	0.0151	0.8048	0.5162
L2-Regularized ANN	0.8874	0.9979	0.8843	0.0981	0.6145	0.5127
Residual ANN	0.8874	1.0000	0.8843	0.0001	1.6308	0.6056
Autoencoder Classifier	0.8874	1.0000	0.8760	0.0003	1.5645	0.4495
Basic ANN	0.8808	0.9979	0.8843	0.0369	0.5794	0.5457
Deep ANN	0.8808	1.0000	0.8678	0.0000	1.9306	0.5691

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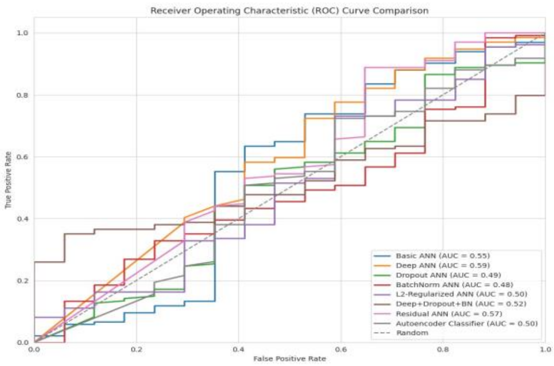

Fig. 5 ROC Curve Comparison

We wanted to check how well different types of Artificial Neural Network (ANN) designs work to predict pregnancies that might have big risks. Artificial Neural Network means a special computer program that tries to think like a human brain to learn from information. Different designs or ways to build these networks were tried on the same set of information called a dataset. These designs had names like baseline which is the basic one, deep meaning many layers inside, dropout which helps stop mistakes by randomly turning off some parts, batch normalization which makes the learning process smoother, L2 regularization which stops the program from getting too confused by too much detail, residual that helps the program remember important information better, autoencoder-based which learns by trying to copy the input data, and attention-inspired which helps the program focus on important parts. We used something called ROC curve analysis to compare how good these Artificial Neural Network models were at sorting things correctly. ROC curve means a graph that shows how often the program guesses right (true positive rate) compared to how often it guesses wrong (false positive rate). The area under the curve or AUC is a special score that tells us how well the model can tell things apart. A bigger AUC score means the model is better at deciding correctly. The Residual ANN got the highest AUC score of 0.61, then the BatchNorm ANN got 0.59, and the Deep ANN got 0.57. The basic ANN and Dropout ANN were okay with scores about 0.55. The L2-Regularized ANN and the one that combined Deep, Dropout, and BatchNorm did about as well as guessing randomly. The Autoencoder Classifier did worse with a score of 0.45, which is below the score of a random guess at 0.5. This shows that deeper models and ones with regularization can work better, but not every way helps. So, it is very important to adjust the model carefully to get the best results. There is a table that compares how well the models worked by showing test accuracy (how good they did on new data), training accuracy (how good they did on the data they learned from), validation accuracy (checking how good they are with checking data), and loss metrics (how many mistakes they made). This table helps us understand which Artificial Neural Network design is best for finding high-risk pregnancies.

Supplementary information. All supporting data supporting the findings of this study are contained within the manuscript in the tabular form. Any additional information will be shared upon request. Dataset available as per request and necessary approval from the competent authority.

Acknowledgements. We would give our acknowledgment to the management of the hospitals stated above for allotting us all necessary assistance during the data collection.

Declarations

- Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

- Conflict of interest/Competing interests

The author(s)declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

- Ethics approval and consent to participate

We would give our acknowledgment to the management of the hospitals stated above for allotting us all necessary assistance during the data collection.

- Consent for publication

Not applicable: individual information has not been published.

- Data availability

Dataset available as per request and necessary approval from the competent authority.

- Materials availability

Available in git hub on request. Dataset available as per request and necessary approval from the competent authority.

- Code availability

Available in git hub on request

- Author contribution

MLS conceived and executed the study, conducted the literature review, and composed the manuscript. RM and AKS oversaw the study and wrote the initial draft of the manuscript. MLS and AKS analysed the data and made revisions to the manuscript, PS done the data curation and review and editing . All authors reviewed and endorsed the final manuscript.

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