2025 International Conference on Intelligent Systems and Computational Networks (ICISCN)

A Meta-learner Based Ensemble System of Neural Networks for Improving the Accuracy of Preterm Birth Prediction

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***Abstract*— The birth in which the babies born during 37th, 38th or 39th weeks are considered as Term Births (TB). On the other hand, earlier births are considered as Preterm Births (PTB) and the latter births are considered as Late-term Births or Post-term Births. The risk of neonatal death is very high in PTB. The objective of this study is to introduce an Ensemble System of Neural Networks (ESNN) for improving the accuracy of predicting PTB. This study builds an ensemble system that combines the output of multiple neural networks with different configurations to predict the PTB. A meta learner is used as the combination scheme to arrive at the final output. Choosing a set of suitable base configurations with optimal values set for the hyper-parameters and a suitable meta learner result in improving the accuracy of predicting PTB. Experimental results reveal that ESNN achieves an accuracy of more than 94%. This system can help the O&G consultants to accurately diagnose the preterm birth and medicate the expectant mother well in advance so that the birth can be delayed, to convert PTB to TB.**

***Keywords*—** *Preterm Birth, Term Birth, Neonatal Death, Perinatal Mortality Rate, Risk Factors associated with PTB, Ensemble Learning, Neural Network, Hyperparameters, Activation Functions, Meta-Learner.*

I. INTRODUCTION (*HEADING 1*)

In developed countries like USA, UK, etc., the quality of maternal and newborn care is assessed using an important indicator called Perinatal Mortality Rate (PMR) [1].

$$PMR = \frac{x}{x + y} \quad \text{(Eq. 1)}$$

Where ‘x’ refers to the number of Fetal Deaths after 28 weeks of gestation and before 7 days of birth and ‘y’ refers to the total number of live births. PTB is one of the primary reasons for bloating PMR, in developed countries [2]. As per the Surveillance report from MBRRACE-UK published in 2019, for every 150 births, there was one perinatal or neonatal death [6-8]. Though there was a reduction of 12% in PMR from 2013 to 2017, it requires lot more focus on diagnosing and handling the PTB cases. There are many researches that are currently going on to reduce PTB cases and thus to reduce PMR. Reducing the PMR will in turn reduce the health care index of the country and reflect the better state of the country when it comes to providing quality health care to its people.

Depending upon the duration it takes for the birth of babies, they are termed as either Term Birth (TB) or Preterm Birth (PTB). Births that occur either in the 37th, 38th or in the 39th week are termed as TB. PTB refers to the births that occur before 37 weeks of gestation [3]. In some rare cases, post term birth also occurs, i.e. birth after 39 weeks of gestation. As depicted in Table I., there are four types of PTB based on how earlier the birth occurs.

TABLE I. PRETERM BIRTH TYPES

PTB Type	Description	Remarks
Late PTB	Between 34th and 36th week	Requires incubation, breast feeding support and basic care for infection.
Moderately PTB	Between 32nd and 34th week	Suffers complications like sensory deficits, learning disabilities, etc.
Very PTB	Between 28th and 32nd week	Suffers complications like respiratory problems, brain injury, cerebral palsy, etc.
Extremely PTB	Before 28th week	Probability of Mortality is very high.

There are certain factors that seem to increase the susceptibility of a particular disease, and are called as the risk factors associated with that disease. In line with this, PTB has got a set of risk factors and they are classified under two heads namely Primary Risk Factors and Secondary Risk Factors. Primary Risk Factors are said to have high influence on the level of PTB. Fig. 1. and Fig. 2. depict the primary and secondary risk factors of PTB respectively [4].

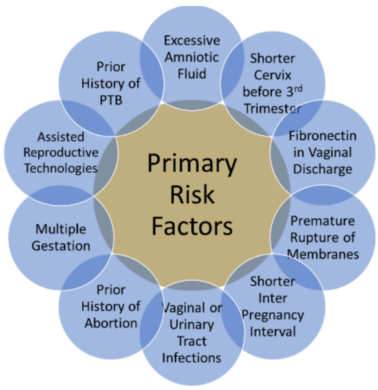

Fig. 1. Primary Risk Factors of PTB

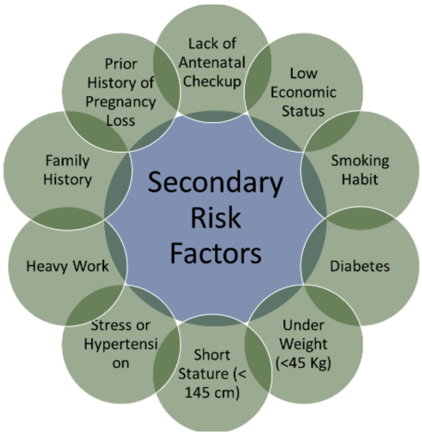

Fig. 2. Secondary Risk Factors of PTB

In the fact sheet published by WHO, it is stated that, around the world, more than 10% of the babies born are very much before the standard mark of 37 weeks of gestation. Over the past 20 years, in most of the countries, this rate is increasing year on year. Though Africa and South Asia contribute for nealy 60% of PTB, it is a universal problem. The developed countries like USA, UK, etc. are partly successful in converting Late PTB or Moderately PTB to TB and they are still searching for ways to control the Very PTB and Extremely PTB.

One of the major challenges in reducing the PTB is that 60% of the PTB cases are spontaneous and thus the time available for efficient medical intervention to delay the labor is very less. Hence converting PTB to term birth becomes almost impossible in most of the cases. Even in non-spontaneous cases (indicated PTB), the clinical evidence for PTB is observed only after 30 weeks. As the spontaneous PTB contributes heavily to Perinatal Mortality, there is a great need to use some statistical models (prediction models) to predict the PTB during early weeks of gestation itself.

Though there are many ways of building statistical models for prediction, using neural networks is very promising and it helps to build better models with good generalizing capabilities for unseen examples and hence they achieve higher performance. This chapter introduces an innovative ensemble learning system that combines the predictions from multiple neural networks using a meta learner. It uses the decision tree classifier as the meta learner. Neural networks with multiple configurations are used as base classifiers of the ensemble system.

The following are the contributions of this study: (i) introduce ESNN to improve the prediction accuracy (ii) Use ESNN to predict the PTB accurately and (iii) motivate the research community to use ESNN for other classification problems. Organization of the remaining sections: Section 2 describes the related work carried out in predicting the PTB. Section 3 gives the background about ensemble learning and introduces the proposed methodology for predicting PTB. The results of the various experiments conducted in this study and the inferences derived from those results are articulated in section 4 and section 5 depicts the conclusion and the scope for future work.

II. Related Work

In the field of OG, PTB is considered as one of the hot areas for research. Due to this fascination, there is an increasing trend in the number of studies across the world that explores different facets of predicting PTB. More than 60% of these studies analyze the peeks and troughs in the EHG signals to predict PTB and the rest of the studies use data analytics approach using historical data of PTB. In the last 10 years, predictive analytics has been widely used in the field of OG for predicting many labor complications. There are many popular algorithms that have been used for predicting PTB. The rest of this section highlights the key researches that have been carried out to predict PTB.

Paul Fergus et al. [5] used Fast Discrete Fourier Transform (FT) to get the frequency representation of the EHG (Electrohysterogram) signal. This study accessed Physionet database for the EHG dataset. It extracted 12 linear features from the EHG signals and filtered a specific band of frequency (0.34 to 1 Hz) using analogue three pole Butterworth filter. In order to find out the best network for classifying PTB, they trained seven networks with 12 features extracted from EHG signals. The classifiers used in their study were: the back-propagation trained feed-forward neural network classifier (BPXNC), Levenberg–Mar- quardt trained feed-forward neural network classifier (LMNC), the perceptron linear classifier (PERLC), radial basis function neural network classifier (RBNC), random neural network classifier (RNNC), the Voted Perceptron Classifier (VPC) and the Discriminative Restricted Boltzmann Machine classifier (DRBMC). It used K-fold Cross-validation technique for assessing the accuracy of the classifiers. Based on the experimental results it concluded that RBNC was the best performing classifier. Utilizing oversampling to increase the number of preterm samples is the downside of this study.

Peng Ren et al. [6] used an analytical approach to predict the PTB based on the electromyography (EMG) recordings. This study applied the Empirical Mode Decomposition to extract the Intrinsic Mode Functions. From the first ten functions, the entropy values were amplitude and frequency were extracted and used as the features for predicting the PTB. It used TPEHG dataset that consisted of 262 TB instances and 38 PTB instances. To remove the class imbalance, synthetic minority over-sampling technique (SMOTE) was used. Six classifiers namely support vector machines (SVM), Random Forest (RF), multilayer perceptron (MLP), Adaboost, Bayesian Network and simple logistic regression (SLR) were used for prediction. Among the six classifiers, Adaboost achieved the highest performance of 98.6% are under the curve (AUC). The study did not disclose about other important performance measures like Accuracy, Precision, etc.

Franc Jager et al. [7] used a combination of EHG and Tocogram signals for predicting PTB.This study used TPEHG database for classifying the signals. This study extracted the features like sample entropy, the median frequency, peak amplitude. This study analyzed the peak amplitude of the maternal heart rate to assess how far the delivery is. Extracting the features for dummy intervals provided better features than extracting the features for contraction intervals. It achieved a performance of 100% accuracy for expectant mothers who were in the 23rd week of their pregnancy. Though it achieved high accuracy, the testing was not done for wide range of signals.

Jean-Baptiste Tylcz et al. [8] used EHG signals to classify the births as PTB or TB. The study extracted the statistical features from this signal using Gausian Mixture Models and a non-linear correlation analysis. This study used a dataset comprising of EHG signals of 68 expectant mothers. By analyzing the variations observed in EHG signals, it achieved an accuracy of 80.7% for clssifying the uterine contraction as PTB or TB. As the number of signals used for analysis was as low as 68, the generalization capability of the model is very low. Thus, it may not achieve high performance for the unseen signals.

Urvi Tanna Wadhawan et al. [9] carried out an observational study of 100 expectant mothers. This study monitored the cervical length of the expectant mothers in the first trimester and the second trimester. The average length of the cervix length in the first trimester was 3.94 cm and the same in the second trimester was 3.38 cm. The study found that 12% of the expectant mothers whose cervix shortened from the first trimester to second trimester delivered the babies in PTB. The study concluded that there is an inverse relation between the cervix length and the frequency of PTB. The only flip side of this study is that it focused only on cervical length.

III. Material and Methods

Ensemble technique trains two or more standalone classifiers and uses combination schemes to arrive at the final decisions [10]. When standalone classifiers that produce wrong predictions for different sets of instances within the datasets are used in ensemble systems, the strength of one classifier makes up for the weakness of another classifier and thus results in improved performance of the ensemble systems [11]. Hence the misclassification rate reduces drastically when compared with the individual systems. There are two major types of ensemble systems namely Homogeneous Systems and Heterogeneous Systems. When a single classifier with either different input space or different configurations is combined to build ensemble systems, it is termed as Homogeneous systems. When different classifiers with either same input space or same configuration are combined to build ensemble systems, it is termed as Heterogeneous systems.

In day-to-day life, most of the people make their decision based on the opinions of the friends/family members/experts. They weigh the pros and cons of these opinions and consolidate these opinions to arrive at the decisions. Ensemble learning also uses the same principle. The performance of Ensemble Systems are better than the standalone classifiers for most of the real-world problems and hence are preferred over a single classifier [12].

This study proposes an innovative ensemble learning methodology that combines the predictions of multiple neural networks with different configurations. Using a single neural network for predicting PTB leads to the problem of arriving at the local minima of errors rather than finding the global minima of errors. Hence using multiple neural networks with different set of configurations and combining them using a combination scheme increases the probability of finding the global minima of errors. This is mainly due to the fact that combining the neural networks with different configurations complements each other and compensates for their weakness.

The performance of any ensembled algorithm is fully dependent on diversity of the classifiers that constitute the ensemble system and the choice of the combination scheme used for arriving at the final decision. In ESNN, the variation in the configuration of neural network ensures that there is enough diversity in the base classifiers and the weighted majority voting can combine the individual decisions without much bias. ESNN is implemented with two tier architecture and has the components as depicted in Fig. 3.

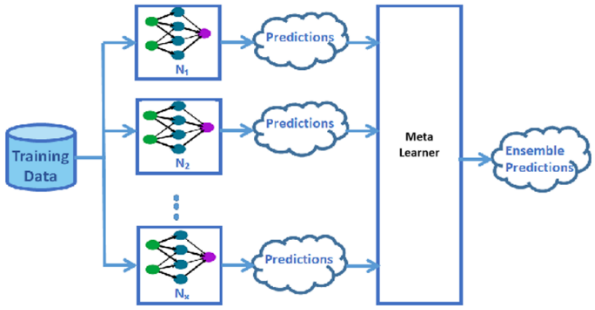

Fig. 3. Architecture of ESNN

In ESNN, Multi-Layer Perceptron (MLP) is used as the base classifier. A perceptron is a binary classification algorithm that divides the input space into two parts namely 0 or 1. A perceptron takes a set of inputs and finds their weights based on importance of each of the inputs and combines them in a linear manner to produce the output. In order to convert the output to a binary class label, it uses an activation function. A simple perceptron has only two layers: input layer and output layer. When perceptron are stacked in multiple layers, it becomes a MLP and it may be either deep or shallow depending upon the number of hidden layers. MLP is a feed forward artificial neural network in which the number of hidden layers, number of nodes in the hidden layer, the activation function and the initial weights can be configured.

In this study, MLPs with 12 different configurations have been trained. Each of these configurations have different values for the four hyper-parameters of the network. The hyper-parameters are: Number of Hidden Layers, Number of Hidden Nodes, Activation Function and the Initial Weights. In all these configurations the biases are initialized with zero value. Table II. depicts the details about each of these configurations.

TABLE II. Neural Network Configurations (Base Classifiers)

Configuration	**# of Hidden Layers**	**# of Hidden Nodes**	**Activation Function**	**Initial Weights**
NN1	4	2	Sigmoid	Random Initialization
NN2	4	2	TanH	Xavier Initialization
NN3	4	2	ReLU	He Initialization
NN4	4	3	Sigmoid	Random Initialization
NN5	4	3	TanH	Xavier Initialization
NN6	4	3	ReLU	He Initialization
NN7	6	2	Sigmoid	Random Initialization
NN8	6	2	TanH	Xavier Initialization
NN9	6	2	ReLU	He Initialization
NN10	6	3	Sigmoid	Random Initialization
NN11	6	3	TanH	Xavier Initialization

NN12	6	3	ReLU	He Initialization

Activation function is used to transform the output values to binary values i.e. either [0,1] or [-1,1]. ESNN uses one among the three activation functions namely: Sigmoid Function, Hyperbolic Tangent Function and Rectified Linear Units.

Sigmoid Function: This function transforms the output values to [0,1]. When plotted it gives a S-shaped curve. This function is of the form:

$$S(x) = \frac{1}{1 + e^{-x}} \qquad \text{(Eq. 2)}$$

Hyperbolic Tangent Function: This function transforms the output values to [-1,1]. When plotted it also gives a S-shaped curve. This function is of the form:

$$T(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \qquad \text{(Eq. 3)}$$

Rectified Linear Units (ReLU): It transforms all positive values into 1 and all negative and zero values into 0. This function is of the form:

$$G(x) = \max(0, x) \qquad \text{(Eq. 4)}$$

Weight Initialization: As with any stochastic optimization algorithm, neural networks also require the weights to be initialized with some random values.

Issues with Random Initialization: If the random values are too large or too small, the convergence of loss function takes very long time and also it leads to vanishing/exploding gradient problem. Hence there is a need to initialize with near optimal values. Xavier and He initializations are used to overcome vanishing/exploding gradient problem by initializing the weights with near optimal values.

Xavier Initialization: The random values are multiplied with 1/ √ N where N is the number of observations in the training data. The weight is typically chosen from a random uniform distribution that has the following boundary:

$$\pm\sqrt{\frac{n}{n_i + n_{i+1}}}$$

He Initialization: The random values are multiplied with 2/ √ N where N is the number of observations in the training data.

The predictions from the neural networks of basic configurations were ensembled using the Decision Tree Classifier (DTC). As the predictions from the base classifiers were either 0 or 1, it was thought that DTC as the meta learner would be an idea choice. Moreover, the number of base classifiers were limited to 12 and hence the size of the tree was very much manageable.

In order to carry out the experiments for this study, the data was collected from a hospital specializing in OG. The dataset had a good proportion of PTB cases in it. The results from various tests carried out on expectant mothers during the first and second trimesters and the observation by the OG consultant were captured in this dataset. In order to ensure the security of patients data, all the features related to personal identities were either removed or masked. Thus the questions from ethical committee were avoided and the data was used without much constraints. As depicted in Table III., the dataset had an imbalance ratio of 2.92.

TABLE III. DATASET DETAILS

# of Instances	**2600**
# of Attributes	26
# of Classes	2
# of Major Instances	1936
# of Minor Instances	664
Imbalance Ratio (IR)	2.92

After careful analysis, the above instances were chosen for this study from a larger dataset so that the chosen instances cover the following.

- Expectant mothers who had three or more primary risk factors and delivered the baby in PTB
- Expectant mothers who did not have any of the primary risk factors and delivered the bay in PTB
- Expectant mothers who had three or more primary risk factors and delivered the baby in TB
- Expectant mothers who did not have any of the primary risk factors and delivered the bay in TB

As part of pre-processing of data, the dataset was cleaned up, to replace the missing values in each of the features with median of the corresponding features. For all the numeric features, outlier analysis was carried out and the outliers were replaced with largest values (without outlier) of the corresponding features. The dataset was standardized using z-score transformation.

$$Z\ Score = \frac{x - \bar{x}}{\sigma} \qquad \text{(Eq. 5)}$$

To find out the critical risk factors that contribute heavily to PTB, different experiments were carried out. Table 4. depicts the list of experiments carried out in this study.

TABLE IV. LIST OF EXPERIMENTS

Sl. No.	Experiment	Description
1	Only Primary	All the features from the primary risk factors
2	Top 5 Primary	Top 5 features from the primary risk factors
3	Only Secondary	All the features from the secondary risk factors
4	Top 5 Secondary	Top 5 features from the secondary risk factors
5	All Factors	All the risk factors
6	Primary and Secondary	Top Five Primary and Top Five Secondary Risk Factors

The dataset was split into two sets at 70% and 30% to create the set for training the model and the set for testing the model. This ensured that unseen instances in the test set were used to test and to measure the performance of the prediction. To ensure the validity of comparison of results across the experiments, the same training set and the test set were used across the experiments. Thus, the random sample were taken only once before the experiments were conducted.

ESNN was implemented using Scikit-learn library in Python. As the number of TB instances is almost three times the number of PTB instances, the dataset is an asymmetric dataset and it is skewed towards TB. Any skewed dataset needs to be balanced either by increasing the number of minority instances or by purging some of the majority instances. Synthetic Minority Oversampling Technique (SMOTE) is a popular approach for balancing the skewed datasets by adding few minority instances. SMOTE algorithm creates new synthetic samples that have the same statistical properties of the underlying distribution of the dataset. Hence the introduction of new samples does not distort the probability distribution and hence make the results more reliable. The comparison of how the instances have increased in dataset by applying SMOTE is depicted in Fig. 4.

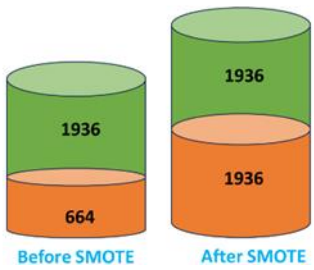

Fig. 4. Balancing the Dataset

IV. RESULTS AND DISCUSSION

As depicted in Table 5. And Fig. 5., for all the experiments conducted, this study recorded the accuracy, precision, recall and F1-Score for ESNN and the individual networks. Since it is essential to ensure the consistency of results, the results from 10 trials of all the experiments were captured. The mean values and the standard deviation of the metrics across the trials were reported here. The results with respect to these metrics were analyzed to find out whether ESNN outperforms the individual neural networks with basic configurations. Without the need for using feature engineering techniques to select the features, when all the features were used, the performance of ESNN reaches its peak. At the same time, the performance difference between ESNN and the individual Neural Networks with basic configurations is at the maximum for experiment 2. The outcome of this analysis has revealed that the top 5 primary risk factors contribute more for PTB. In all the sets of experiments, ESNN outperformed the individual neural networks with basic configuration and thus ESNN is the suitable methodology for predicting PTB.

TABLE V. RESULT SUMMARY

Experiment	Accuracy	Precision	Recall	F1-Score
1	92.3±0.08	90.9±0.11	91.4±0.12	91.1±0.04
2	94.6±0.07	92.8±0.06	93.2±0.03	93.0±0.02
3	91.7±0.13	89.9±0.16	91.1±0.15	90.5±0.11
4	93.6±0.09	92.1±0.13	91.9±0.12	92.0±0.08
5	89.9±0.23	88.7±0.19	89.1±0.21	88.9±0.19
6	90.8±0.12	90.1±0.16	089.9±0.11	90.0±0.12

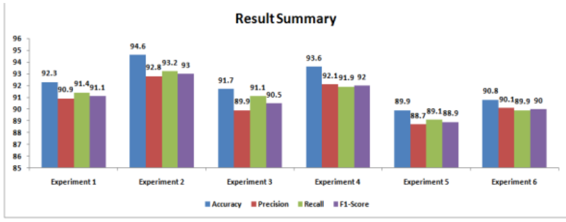

Fig. 5. Result Summary

A comparison of the results of each of the experiments for ESNN and the individual Neural Networks is depicted in Fig. 6. In all the experiments, ESNN outperformed the individual networks in all the performance metrics. Especially when only the top5 primary risk factors were used, the performance difference between ESNN and the individual networks is as high as 6%.

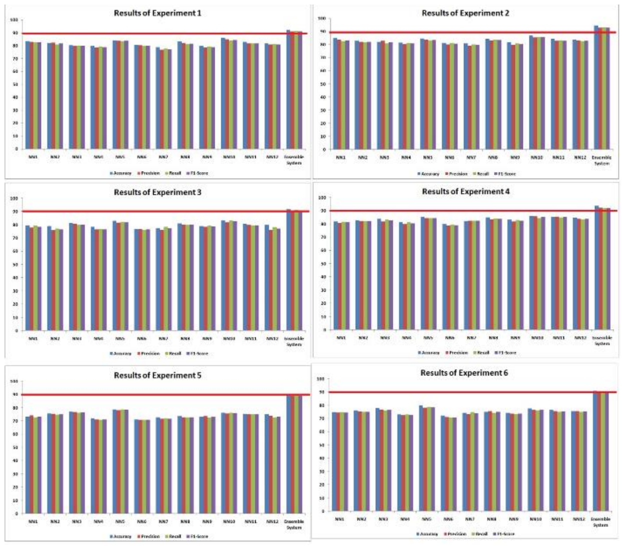

Fig. 6. Results of Six Experiments

The results obtained from six experiments were analyzed thoroughly to find out in which experiment(s), the performance of ESNN overshadows the individual Neural Networks with Basic Configurations (base classifiers). As depicted in Fig. 7., in experiments 1, 2, 5 & 6, the performance difference between ESNN and the base classifiers is relatively higher than that in experiments 3 & 4. Though ESNN outperforms in these experiments (3 & 4) also, the performance difference was not considerable when compared to other four experiments. This reveals that the secondary risk factors are poor indicators of PTB when used in isolation. Hence, building prediction models only with secondary risk factors is not going to help in predicting PTB accurately. When the top five secondary factors were used for predicting PTB, the accuracy is lower than the accuracy achieved by other experiments. This is primarily due to the fact that the generalization is bit challenging with secondary risk factors when compared with primary risk factors. On the other hand, ESNN outperforms significantly with top 5 primary risk factors. Thus, the secondary risk factors contribute in an insignificant manner to PTB.

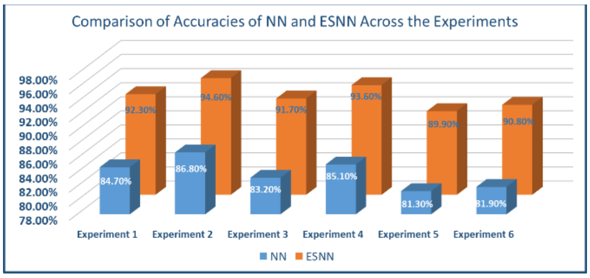

Fig. 7. Analysis of Accuracy across the Experiments

An analysis of the 12 individual neural networks were carried to find out the top performing network. The performance of this network is compared with ESNN along all the performance metrics. As depicted in Figure 8., ESNN has outperformed the NN with basic configuration in terms of all the metrics. Hence ESNN is way ahead of the individual networks for predicting PTB.

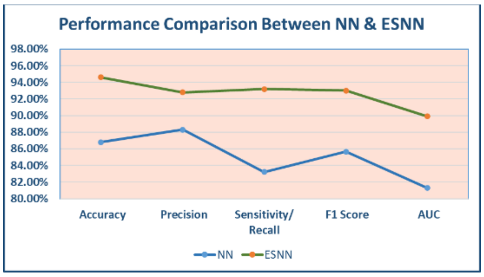

Fig. 8. Analysis of Performance

Thus, ESNN not only gives a good performance and is also superior than NN in terms of all the metrics. Even though much of the comparison was performed for Experiment Number 2, primary risk factors like Presence of Fibronectin, Excessive Amniotic Acid, prior history, premature rupture and shorter cervix were used, the performance of ESNN is very much in similar terms for all other experiments as well.

V. Conclusion

ESNN gives a better performance than the individual Neural Networks with the Basic Configuration for all the scenarios under consideration. This is not just true for accuracy alone, it is true for all the performance metrics measured in this study. Presence of Fibronectin, Excessive Amniotic Acid and shorter cervix are the top risk factors that determines whether a birth is TB or PTB. Though the usage of secondary factors like Diabetes, genetics, prior history of PTB along with the primary risk factors improves the accuracy marginally, to determine their actual impact on PTB and on time complexity, a deeper look into the results is required. This study concludes that PTB is majorly determined by the primary risk factors. The time complexity of the proposed algorithm with different set of factors like number of neural network can be considered for the future work. As ESNN is scalable in terms of the number of neural networks, the performance can further be improved by using a large number of neural networks by training them in parallel. Another exciting area to explore further is that the optimization of number of neural networks and the optimization of configurations of the neural networks.

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