EARLY GESTATIONAL DIABETES DETECTION THROUGH NEURAL NETWORK

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STUDENT'S DECLARATION

I hereby declare that this thesis has not been submitted elsewhere for the requirement of any kind of degree, diploma or publication.

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SUPERVISOR'S DECLARATION

I hereby declared that I've checked this thesis in my opinion, this thesis is adequate in terms of scope and quality for award of the degree of Bachelor of Science in Information and Communication Engineering.

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Abstract

Gestational Diabetes Mellitus (GDM) is defined as any degree of glucose intolerance with onset or first recognition during pregnancy. Fifty percent of GDM patients develop type 2 Diabetes in next twenty years and as well as the newborn can also be affected by diabetes in their lifetime. So the long term complications for both the mother and the child cannot be ignored. In view of maternal morbidity and mortality as well as fetal complications, early diagnosis is an utmost necessity in the present scenario. In developing country like Bangladesh, early detection and prevention is more cost effective and troublesome. So there is an urgent need for a well-designed method for the detection of gestational diabetes mellitus. The purpose of this study is to predict the GDM in the first trimester. This research presents and compares some Artificial Neural Network (ANN) models on the early detection of Gestational diabetes mellitus and chooses the best neural network model among them to detect GDM early.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ADA	American Diabetes Association
AutoMLP	Automatic Multilayer Perceptron
ANN	Artificial Neural Network
ASFT	Abdominal Subcutaneous Fat Thickness
BMI	Body Mass Index
BP	Back Propagation
BPN	Back Propagation network
CBFCM	Case Based Fuzzy Cognitive Map
DM	Diabetes Mellitus
GA	Genetic Algorithm
GCT	Glucose Challenge Test
GDM	Gestational Diabetes Mellitus
GLMM	Generalized Linear Mixed Model
GP	Genetic Programming
MLPNN	Multilayer Perceptron Neural Network
MAE	Mean Absolute Error
MSD	Mean Squared Deviation

MSE	Mean Square Error
NMSE	Normalized Mean Square Error
OGTT	Oral glucose tolerance test
PCOS	Polycystic Ovarian Syndrome
PGR	Plasma Glucose Response
RBFNN	Radial Basis Function Neural Network
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SOM	Self-Organizing Feature Map
SVM	Support Vector Machine

CHAPTER 1

INTRODUCTION

1.1 Diabetes

Diabetes mellitus (DM) is the condition in which the body does not properly process food for use as energy. Most of the food we eat is turned into glucose, or sugar, for our bodies to use for energy. The pancreas, an organ that lies near the stomach, makes a hormone called insulin to help glucose get into the cells of our bodies. When we have diabetes, our body either doesn't make enough insulin or can't use its own insulin as well as it should. This causes sugars to build up in our blood. This is why many people refer to diabetes as “sugar”.

Diabetes mellitus (DM), commonly referred to as diabetes, is a group of metabolic disorders in which there are high blood sugar levels over a prolonged period. Symptoms of high blood sugar include frequent urination, increased thirst, and increase hunger. If left untreated, diabetes can cause many complications. Acute complications can include diabetic ketoacidosis, hyperosmolar hyperglycemic state, or death. Serious long-term complications include cardiovascular disease, stroke, chronic kidney disease, foot ulcers, and damage to the eyes.

1.1.1 Symptoms

The classic symptoms of untreated diabetes are weight loss, polyuria (increased urination), polydipsia (increased thirst), and polyphagia (increased hunger). Symptoms may develop rapidly (weeks or months) in type 1 DM, while they usually develop much more slowly and may be subtle or absent in type 2 DM.

Several other signs and symptoms can mark the onset of diabetes although they are not specific to the disease. In addition to the known ones above, they include blurry vision, headache, fatigue, slow healing of cuts, and itchy skin. Prolonged high blood glucose can cause glucose absorption in the lens of the eye, which leads to changes in its shape, resulting in vision changes. A number

of skin rashes that can occur in diabetes are collectively known as diabetic dermadromes. Low blood sugar (hypoglycemia), is common in persons with type 1 and type 2 DM. Most cases are mild and are not considered medical emergencies. Effects can range from feelings of unease, sweating, trembling, and increased appetite in mild cases to more serious issues such as confusion, changes in behavior such as aggressiveness, seizures, unconsciousness, and (rarely) permanent brain damage or death in severe cases. Moderately low blood sugar may easily be mistaken for drunkenness rapid breathing and sweating, cold, pale skin are characteristic of low blood sugar but not definitive. Mild to moderate cases are self-treated by eating or drinking something high in sugar. Severe cases can lead to unconsciousness and must be treated with intravenous glucose or injections with glucagon.

People usually with type 1 DM may also experience episodes of diabetic ketoacidosis, a metabolic disturbance characterized by nausea, vomiting and abdominal pain, the smell of acetone on the breath, deep breathing known as Kussmaul breathing, and in severe cases a decreased level of consciousness. A rare but equally severe possibility is hyperosmolar hyperglycemic state, which is more common in type 2 DM and is mainly the result of dehydration.

1.1.2 Types

Diabetes mellitus is classified into four broad categories: type 1, type 2, gestational diabetes, and "other specific types". The "other specific types" are a collection of a few dozen individual causes. Diabetes is a more variable disease than once thought and people may have combinations of forms. The term "diabetes", without qualification, usually refers to diabetes mellitus.

Type 1 Diabetes

Type 1 diabetes occurs when the immune system mistakenly attacks and kills the beta cells of the pancreas. No, or very little, insulin is released into the body. As a result, sugar builds up in the blood instead of being used as energy. About 10 per cent of people with diabetes have type 1 diabetes. Type 1 diabetes generally develops in childhood or adolescence, but can develop in adulthood. Type 1 diabetes is always treated with insulin.

Type 2 Diabetes

Type 2 diabetes occurs when the body can't properly use the insulin that is released (called insulin insensitivity) or does not make enough insulin. As a result, sugar builds up in the blood instead of being used as energy. About 90 per cent of people with diabetes have type 2 diabetes. Type 2 diabetes more often develops in adults, but children can be affected.

Gestational Diabetes

A third type of diabetes, gestational diabetes, is a temporary condition that occurs during pregnancy. Between three to 25 percent of pregnant women develop gestational diabetes, depending on their risk factors. Having gestational diabetes may increase the risk of developing diabetes for both mother and child. This research focuses on the early detecting of Gestational Diabetes Mellitus (GDM) that is described below in details.

Other type's diabetes

Prediabetes indicates a condition that occurs when a person's blood glucose levels are higher than normal but not high enough for a diagnosis of type 2 DM. Many people destined to develop type 2 DM spend many years in a state of prediabetes. Other forms of diabetes mellitus include congenital diabetes, which is due to genetic defects of insulin secretion, cystic fibrosis-related diabetes, steroid diabetes induced by high doses of glucocorticoids, and several forms of monogenic diabetes.

1.2 Gestational diabetes Mellitus (GDM)

Gestational diabetes mellitus (GDM) is a condition which is quite separate from the other types of diabetes: type 1 and type 2. The term gestational refers to it occurring during pregnancy. For many women who are diagnosed, the diabetes will go away after their baby is born. However, there is a greater risk of developing type 2 diabetes for women who have already had gestational diabetes. Gestational diabetes occurs in up to 25% [1] of all pregnancies and of these women:

1. Type 2 diabetes can develop between 5-10 years after their baby is born.
2. More than 50% of women who had gestational diabetes will develop type 2 diabetes.
3. Following the baby's birth, a mother's blood glucose level generally returns to normal.

Figure 1.1 Diabetes in pregnancy

At around the 20th week of gestation, the usual processes and actions involved in insulin production become affected by pregnancy hormones. This is why gestational diabetes screening tests are done routinely for all women who are pregnant, whether they have a history or not. The most common time for it to occur is between weeks 24-28 of pregnancy, though it is still possible to be diagnosed a few weeks either side of this time frame. As her pregnancy progresses, a mother's need for glucose increases. This is because her energy requirements also increase. In the ideal situation there is sufficient insulin produced to cope with the rise in glucose, but this doesn't always happen. Gestational diabetes is a condition in which a woman without diabetes develops high blood sugar levels during pregnancy. Gestational diabetes generally results in few symptoms; however, it does increase the risk of pre-eclampsia, depression, and requiring a Caesarean section. Babies born to mothers with poorly treated gestational diabetes are at increased risk of being too large, having low blood sugar after birth, and jaundice. If untreated, it can also result in a stillbirth. Long term, children are at higher risk of being overweight and developing type 2 diabetes. Gestational diabetes is caused by not enough insulin in the setting of insulin resistance. Risk factors include being overweight, previously having gestational diabetes, a family history of type 2 diabetes, and having polycystic ovarian syndrome (PCOS). Diagnosis is by blood tests. For those at normal risk screening is recommended between

24 and 28 weeks' gestation. For those at high risk testing may occur at the first prenatal visit. It is especially common during the last three months of pregnancy. According to the American Diabetes Association (ADA), gestational diabetes affects 18 percent of pregnant women. It affects 1% of those under the age of 20 and 13% of those over the age of 44 [1]. A number of ethnic groups including Asians, American Indians, Indigenous Australians, and Pacific Islanders are at higher risk. In gestational diabetes, the hormones that help the baby develop also interfere with the action of the insulin in your body.

1.2.1 Symptoms of GDM

With the release of the latest revelations, symptoms of gestational diabetes are visible years before conception. Several factors lead to this kind of diabetes and controlling these factors can control its onset. Blood sugar and weight of a woman are the biggest tell tales of diabetes. Blood pressure is also one of the causes for the disease. Gestational diabetes symptoms can be subtle or even nonexistent and some can be mistaken for typical side effects of pregnancy, like the urge to pee frequently. Here are some possible signs of gestational diabetes that should be brought to your doctor's attention:

1. Blurred vision
2. Tingling or numbness in the hands and/or feet
3. Excessive thirst
4. Frequent urination
5. Sores that heal slowly
6. Excessive fatigue

1.2.2 Classification of GDM

A woman is diagnosed with gestational diabetes when glucose intolerance continues beyond 24 to 28 weeks of gestation. The White classification named after Priscilla White [2], who pioneered research on the effect of diabetes types on perinatal outcome, is widely used to assess maternal and fetal risk. It distinguishes between gestational diabetes (type A) and pregestational diabetes

(diabetes that existed prior to pregnancy). These two groups are further subdivided according to their associated risks and management.

The two subtypes of gestational diabetes under this classification system are:

1. Type A1: abnormal oral glucose tolerance test (OGTT), but normal blood glucose levels during fasting and two hours after meals; diet modification is sufficient to control glucose levels.
2. Type A2: abnormal OGTT compounded by abnormal glucose levels during fasting and/or after meals; additional therapy with insulin or other medications is required.

1.2.3 Risk factors for developing GDM

Gestational Diabetes Mellitus (GDM) is associated with several maternal and perinatal complications. There are a number of risk factors for gestational diabetes. Classical risk factors for developing gestational diabetes are

1. Polycystic Ovary Syndrome.
2. A previous diagnosis of gestational diabetes or prediabetes, impaired glucose tolerance, or impaired fasting glycaemia.
3. A family history revealing a first-degree relative with type 2 diabetes.
4. Maternal age – a woman's risk factor increases as she gets older (especially for women over 35 years of age).
5. Ethnicity (those with higher risk factors include African-Americans, Afro-Caribbeans, Native Americans, Hispanics, Pacific Islanders, and people originating from Asia).
6. Being overweight, obese or severely obese increases the risk by a factor 2.1, 3.6 and 8.6, respectively.
7. A previous pregnancy which resulted in a child with a macrosomia (high birth weight: >90th centile or >4000 g (8 lbs 12.8 oz)).
8. Previous poor obstetric history.
9. Other genetic risk factors: There are at least 10 genes where certain polymorphism are associated with an increased risk of gestational diabetes.

10. History of contraceptive pill use.
11. Having too much amniotic fluid during pregnancy.

In addition to this, statistics show a double risk of GDM in smokers. Polycystic ovarian syndrome is also a risk factor, although relevant evidence remains controversial. Some studies have looked at more controversial potential risk factors, such as short stature. About 40–60% of women with GDM have no demonstrable risk factor [1]; for this reason many advocate to screen all women. Typically, women with GDM exhibit no symptoms (another reason for universal screening), but some women may demonstrate increased thirst, increased urination, fatigue, nausea and vomiting, bladder infection, yeast infections and blurred vision.

1.2.4 Risks on having GDM

Pregnancy complicated by untreated or poorly treated diabetes is associated with high maternal and peri-natal mortality and several other complications including glucose intolerance and diabetes later in life for both mother and body.

Risks on baby

The mother's inability to produce the right amount of insulin during pregnancy puts the baby at risk in many ways. If GDM presents in the first trimester, this may mean birth defects affecting major organs or an increased risk of miscarriage.

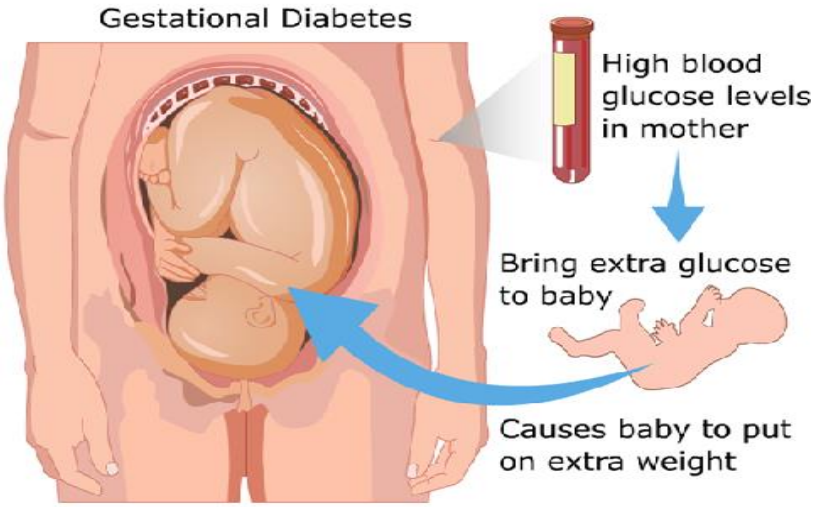

Figure 1.2 Risks on baby having GDM

According to the National Health Service UK website, the following may occur when gestational diabetes is observed in the second or third trimester:

1. Macrosomia – The fetus grows so big (8 pounds and above) that it present problems during labor and delivery. This may result in shoulder dystocia or other birth injuries as well as increased risks for a cesarean delivery.
2. Hypoglycemia – While a low blood sugar level in the baby is pretty common in newborns for the first two hours or so after birth, an extended period in this condition may result in neurological problems, developmental delays and seizures.
3. Jaundice – Baby's skin and eyes are yellow. Though common in newborns, especially among Asian babies, and does not usually indicate a problem, jaundice remains a cause for concern for medical practitioners since it can potentially result in neurological, behavioral and developmental issues.
4. Respiratory Distress Syndrome (RDS) – A baby has trouble breathing and may need medical intervention.

Risks on mother

According to mayoclinic.com [3], the following conditions may occur in mothers with GDM:

1. High blood pressure, preeclampsia and eclampsia – The latter two cause high blood pressure. All 3 pregnancy complications can pose a fatal threat against mom and baby.
2. Future diabetes – Gestational diabetes has a great chance of occurring in the next pregnancy. The mother is also likely to develop type 2 diabetes as she gets older.

1.2.5 Diagnosis

A number of screening and diagnostic tests has been used to look for high levels of glucose in plasma or serum in defined circumstances. Gestational diabetes usually happens in the second half of pregnancy. Doctor will check to see if one have gestational diabetes between weeks 24 and 28 of pregnancy. To test for gestational diabetes, one should quickly drink a sugary drink. This will raise the blood sugar levels. An hour later, a blood test should conduct that the body handled all that sugar. If the results show that blood sugar is higher than a certain cutoff (anywhere from 130 milligrams per deciliter [mg/dL] or higher) [1], patient will need more tests. This means testing patient's blood sugar while fasting and a longer glucose test that will be done over a 3-hour period. If the results are normal

but the patient have a high risk of getting gestational diabetes, she may need a follow-up test later in your pregnancy to make sure she still don't have it.

Non-challenge blood glucose tests

When a plasma glucose level is found to be higher than 126 mg/dl (7.0 mmol/l) after fasting, or over 200 mg/dl (11.1 mmol/l) on any occasion, and if this is confirmed on a subsequent day, the diagnosis of GDM is made, and no further testing is required. These tests are typically performed at the first antenatal visit. They are simple to administer and inexpensive, but have a lower test performance compared to the other tests, with moderate sensitivity, low specificity and high false positive rates.

Screening glucose challenge test

The screening glucose challenge test (sometimes called the O'Sullivan test) is performed between 24–28 weeks, and can be seen as a simplified version of the oral glucose tolerance test (OGTT). No previous fasting is required for this screening test, in contrast to the OGTT. The O'Sullivan test involves drinking a solution containing 50 grams of glucose, and measuring blood levels 1 hour later. If the cut-off point is set at 140 mg/dl (7.8 mmol/l), 80% of women with GDM will be detected. If this threshold for further testing is lowered to 130 mg/dl, 90% of GDM cases will be detected, but there will also be more women who will be subjected to a consequent OGTT unnecessarily.

Oral glucose tolerance test

A standardized oral glucose tolerance test (OGTT) should be done in the morning after an overnight fast of between 8 and 14 hours. During the three previous days the subject must have an unrestricted diet (containing at least 150 g carbohydrate per day) and unlimited physical activity. The subject should remain seated during the test and should not smoke throughout the test. The test involves drinking a solution containing a certain amount of glucose, usually 75 g or 100 g, and drawing blood to measure glucose levels at the start and on set time intervals thereafter.

1.3 Motivation

The fact of diagnosis process of detecting Gestational diabetes Mellitus (GDM) is comparatively time consuming and it is very labored job for a pregnant women to go to the hospital and do all the tests and wait for getting the test report to know whether she has diabetes or no. For this reason more research is needed to find the most effective way of screening for gestational diabetes. Routine screening of women with a glucose challenge test appears to find more women with gestational diabetes than only screening women with risk factors. It is not clear how these screening tests affect the rest of the pregnancy. It is estimated that there will be approximately 18% rise in gestational diabetes prevalence globally [1]. Therefore, there is an urgent need to adopt cost-effective screening and diagnostic methods of gestational diabetes to reduce maternal and fetal complications. This research includes the method of detecting GDM by using various Artificial Neural Network models like Multilayer perceptron neural network (MLPNN), Radial Basis Function Neural Network (RBFNN), Self-Organizing Feature Map (SOM) Neural Network, Support Vector Machine (SVM) Network, Fuzzy Logic and exploring the most efficient model among them.

1.4 Objectives

The objectives of the research are as follows:

1. To develop a cost-effective screening and diagnostic method of detecting gestational diabetes mellitus (GDM) to reduce maternal and fetal complications.
2. To develop different Artificial Neural Network (ANN) models or structures for the early detection of GDM.
3. To study the performance of these network models by applying the same dataset of the patients.
4. To make a comparison among those ANN structures on the basis of finding the best network that shows the more accurate result.
5. To explore the efficient and better ANN structure for predicting the GDM.

CHAPTER 2

LITERATURE REVIEW

The need for an accurate predictor for the gestational diabetes is highly needed. Not only this, but also a predictor that is extremely automated and with less human interference. A diabetic predictor should meet the following specification; efficient modeling, applicability and accuracy and be trusted. It should be compatible with various diagnostic techniques. Many neural network prediction techniques like the Multi-layer perceptron (MLP), Radial basis function (RBF), Support vector machine (SVM), recurrent neural network, Self-organizing feature map network are the most commonly used in the early detection Gestational Diabetes Mellitus (GDM).

Anthropometrical Body surface scanning data was used to construct a classification model for diabetes type II [4]. The model applies four data mining approaches. This model is meant to select and point out the appropriate and necessary decision tree for classifying diabetic diseases. It incorporates Artificial Neural Network, Decision Tree, Logistic Regression and Rough sets.

A research that attempted to enhance the detection of diabetes based on set of attributes collected from the patients developed a mathematical model using Multigene Symbolic Regression Genetic Programming technique [5]. Genetic Programming (GP) showed significant advantages on evolving nonlinear model which can be used for prediction. The developed GP mathematical model was developed to provide a solution to the diabetic problem and to classify patient type. The developed classification accuracy obtained based on Multigene GP is high with respect to sensitivity, specificity, accuracy, positive predicted and negative predicted values. These evaluation criterions proved that Multigene GP is beneficial for diabetic patient classification. They showed 73% accuracy in training and 86% in testing phase.

A work that focused on early detection of GDM for women who are pregnant for the second time onwards (multigravida patients) was proposed and was decided to diagnosis by artificial neural network as the increasing demand of Artificial Neural Network applications for predicting the disease shows better performance in the field of medical decision-making [6]. They used Radial Basis function neural network (RBFNN) technique to classify GDM and non GDM patients with real time data. It was concluded with the early detection and classification of GDM. The GDM diagnosis neural network was modeled using a classification network. Neural Network toolbox of MATLAB R201 Oa was used to develop a c1assification model for GDM data. The problem of diagnosing GDM had been treated as a binary c1assification i.e. the outputs in the model were either 0 or 1. Value 1 was interpreted as "High risk for GDM" and value 0 as "Low risk for GDM".

A model was developed for the prediction of GDM from maternal characteristics and biochemical markers at 11 to 13 weeks' gestation [7]. A prospective screening study on early prediction of pregnancy complications was used to create the predictive model of GDM based on maternal characteristics.

A comparison of the discriminative power of prognostic models for early prediction of women at risk for the development of GDM using four currently recommended diagnostic criteria based on the 75-g OGTT [8]. It was conc1uded by developing a simple prognostic model using age and BMI at booking could be used for selective screening of GDM in Vietnam and in other low- and middle-income settings.

The purpose of a study [9] was to predict GDM in the first trimester. Fasting glucose and insulin were measured in the first trimester and the homeostasis model assessment-insulin resistance index (HOMA-IR) was calculated for each patient. The study included 271 patients who were between the 10th and 14th week of gestation. Fasting glucose and insulin were measured in the first trimester and the homeostasis model assessment–insulin resistance index (HOMA-IR) was calculated for each patient. These values were compared with the results of the second-trimester glucose tolerance test results. HOMA-IR values were higher in women with gestational diabetes. They also were higher in patients treated with diet or diet plus insulin therapy. A cut-off value of 2.60 for HOMA-IR was calculated at the end of the study. Strong positive correlations were observed between HOMA-IR and GDM. A receiver-operating characteristic curve analysis was performed to determine an optimal cut-off value for HOMA-IR in GDM. They compared the cost-

effectiveness of first trimester HOMA-IR with that for the 100-g OGTT at the 24th–28th week of gestation; HOMA-IR was 2.28 times cheaper than the 100-g OGTT.

A semi parametric generalized linear mixed model (GLMM) method was proposed to detect gestational diabetes [10]. This method was applied in evaluating the impact of covariates on the accuracy of diagnostic test results by way of obtaining a common cut off value for screening 50g glucose challenge test (GCT) for the three trimesters of pregnancy.

A paper used fuzzy integral to structure the diagnostic model of gestational diabetes mellitus [11]. The Surgeon measure was obtained by training of Back Propagation (BP) neural network. As the BP neural network is easy to get into local optimum, the algorithm of simulated annealing was used to optimize the BP neural network to obtain an approximate global optimal solution.

A comparison of the diagnostic performances of 75g and 100g Oral Glucose Tolerance Tests in detecting GDM in Nigerian pregnant women [12] and was conc1uded by that 100g OGTT criterion was more stringent than that of75g OGTT in identifying GDM.

A developed a new methodology on Gestational diabetes prediction was developed by using Case Based Fuzzy Cognitive Maps (CBFCM) decision support system [13]. One significant advantage of the proposed CBFCM-based decision-making system over other approaches, such as the Bayesian networks was that it resembles human decision-making, with its capacity for approximate reasoning and handling incomplete information.

A review was conducted on European peer-reviewed literature [14], supplemented by other sources of information, relating to the prevalence of gestational diabetes and current screening practices and barriers to screening. To identify and access the literature, a two-stage search strategy was adopted. The dual search strategies identified 185 separate sources of information from 23 countries, including peer-reviewed research papers, guideline publications and reports from professional and statutory bodies and national registers. Research was sought that reported the prevalence of gestational diabetes in European countries, in so far as possible in nationally representative populations.

An application of hybrid model was presented that integrated Genetic Algorithm (GA) and Back Propagation network (BPN) to classify diabetes mellitus [15] where GA was used to initialize and optimize the connection weights of BPN. Significant features were identified by using two

methods: Decision tree and GA-CFS method were used as input to the hybrid model to diagnose diabetes mellitus. The results proved that, GA-optimized BPN approach had outperformed the BPN approach without GA optimization. In addition the hybrid GA-BPN with relevant inputs lead to further improvised categorization accuracy compared to results produced by GA_BPN alone with some redundant inputs. Application of hybrid GA_BPN had been experimented for classification of PIMA dataset. Back propagation learned by making modifications in weight values by using gradient method starting at the output layer then moving backward through the hidden layers of the network and hence was prone to lead to troubles such as local minimum problem, slow convergence pace and convergence unsteadiness in its training procedure. The hybrid GA_BPN showed substantial improvement in classification accuracy of BPN.

An application of automatic multilayer perceptron (AutoMLP) was developed [16] which was combined with an outlier detection method Enhanced Class Outlier Detection using distance based algorithm to create a novel prediction framework for classifying DM. AutoMLP is an auto-tunable and performs parameter optimization automatically on the run during training process, which otherwise requires human intervention. Their framework performed outlier detection during pre-processing of data. A series of experiments were performed publicly available dataset: UCI (Prima Indian).

A study was performed to verify the correlation between abdominal subcutaneous fat thickness (ASFT) measured by ultrasonography during the first trimester of pregnancy and gestational diabetes mellitus (GDM) of the second trimester in Korean women and to establish a standard of ASFT for predicting GDM [17]. A total of 333 singleton pregnant women participated in that study. Their ASFT was measured by US during the 10+6 to 13+6 weeks of pregnancy; then a GDM confirmatory test (100 g oral glucose tolerance test) was conducted during the 24 to 28 week period of pregnancy. Based on the GDM tests, comparative analyses of the ages of the subjects, pre-pregnancy body mass index (BMI), and weight gain during pregnancy were conducted. The ages of the subjects and weight gains during pregnancy were not correlated to the GDM of the second trimester of pregnancy, but the pre-pregnancy BMIs (22±3.3 kg/m^2) and the ASFT (1.9±0.5 cm) measurements between the control group and subjects during the first trimester of pregnancy were found to show significant differences ($P<0.001$). The cut-off value of the ASFT for predicting GDM was determined to be 2.4 cm (area under the curve=0.90, sensitivity 75.61%, specificity

91.78%, P<0.001). The odds ratio was 2.91 (95% confidence interval, 1.07 to 7.92; P=0.034), which was higher than the 2.4 cm ASFT. It was determined that ASFT as measured by US during the first trimester of pregnancy can be used to predict the risk of developing GDM during the second trimester of pregnancy and for prognosis.

A study was performed among 250 pregnant women aged 15-44 years in their first and second trimester attending antenatal clinics in Ebonyi State University Teaching Hospital, Mile Four Maternity Hospital and Federal Medical Center Abakaliki, Nigeria were seen within the period of June 2010 to December 2011 [18]. Their age, parity, body mass index, gestational age and family history of diabetes were taken, while their gestational diabetes mellitus was assessed using 100g oral glucose tolerance test (OGTT). The plasma glucose response (PGR) was assessed and glucose tolerance status of each patient was interpreted using National Diabetes Data Group criteria. The prevalence of gestational diabetes was determined and its relationship with risk factors compared. The study subjects had a mean gestational age of 26 ±6.4 weeks, mean parity of 1.5 and BMI of 26.5(+/-3.8) kg/m2. The prevalence rate of GDM diagnosed by 100g OGTT was 4.8%. The prevalence of GDM in pregnant women within the age of 15-24years was 3.3%, 25-34years had 4.2% and 3444years had 17.6%. The prevalence of GDM increased significantly with increase in age of the subjects (P = 0.035). Prevalence of GDM according to the gestational age of 1st trimester, 2nd trimester and 3rd trimester were 7.7%, 5.6% and 3.9% respectively. The relationship however was not statistically significant (P = 0.736. The prevalence of GDM according to the parity of the women at 0, 1-4 and ≥5 were 5.1%, 4.1% and 8.0% respectively. The relationship also showed no significant difference (P = 0.689). The women with family history of diabetes had GDM prevalence of 4.5% while those without family history of diabetes had 4.8%. No significant difference was observed (P-value = 0.953). The prevalence of gestational diabetes mellitus in this region of the country was found to be 4.8%.

CHAPTER 3

METHODOLOGY

Diabetes Mellitus is one of the deadly diseases growing at a rapid rate in the developing countries. Diabetes Mellitus is being one of the major contributors to the mortality rate. It is the sixth reason for death worldwide [1]. Gestational Diabetes Mellitus (GDM) can occur temporarily during pregnancy which is due to the hormonal changes and usually begins in the fifth or sixth month of pregnancy, between the 24th and 28th weeks. GDM has increased worldwide and occurs in 1-25% of all pregnancies [1]. Gestational diabetes usually resolves once the baby is born. This figure varies substantially between populations and the diagnostic criteria used. GDM is associated with adverse perinatal outcomes, future development of type 2 diabetes in the mother and an increased risk of the offspring developing obesity and impaired glucose tolerance in childhood and early adulthood. However, 25-50% of women [1] with gestational diabetes will eventually develop diabetes later in their life, especially in those who require insulin during pregnancy and those who are overweight after their delivery. So the early detection of the disease is highly recommended. It is essential to find a way that can help in early predicting this disease.

A model of detecting the GDM with high accuracy, less complex and has efficient performance is urgently needed. To address this need, the method identified in this study offers every pregnant woman the opportunity to know her risk early. Artificial Neural Network (ANN) model is becoming more popular in detecting various diseases so that the risk of the specific disease decreases. The early detection or classification of any disease helps anyone to decrease the risk of the disease. When c1assification is the goal, the artificial neural network (ANN) models often deliver close to the best fit. The present work is motivated in this direction.

3.1 Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is a computational structure that is inspired by observed process in natural networks of biological neurons in the brain. A very important feature of these networks is their adaptive nature, where "Learning by example" replaces "programming" in solving problems. This is a pattern recognition method which can recognize hidden patterns between independent and dependent variables. Neural networks are non-linear statistical data modeling tools and can be used to model complex relationships between inputs and outputs or to find patterns in a dataset. Machine learning and statistical pattern recognition has been the subject of tremendous interest in the biomedical community as these approaches offer promise for improving the sensitivity and specificity of detection and diagnosis of disease. Moreover, these approaches reduce the potential for human error in the decision making process. ANN are widely used for classification and diagnosis in various thirst areas like effective decision making in medical field, signal processing and so on. In biochemical analysis, artificial neural networks have been used to analyze blood samples, track glucose levels in diabetes.

Neurons are connected to each other with a set of links called synapses, and each synapse is desired by a synaptic weight and they interact with each other. Neural network processes three different types of neuron such as input neurons, hidden neurons and output neurons [19]. Neurons are placed in the layer and the neurons of each layer operates in parallel. The first layer is the input layer. The activity of input units represents the non-processed information that entered the network; at that layer neuron does not perform any computations. The hidden layer follows the input layer, and the activity of each hidden unit is determined from the activity of the input units and the weights at the connection of input and hidden units. A neural network model can have many or none hidden layers and their role is to improve the network performance. The last layer is the output layer. The output of the layer is the output of the whole network. Neurons of the output layer, in contrast to input layers perform calculations. The neuron numbers of the external layer is determined with the number of output parameters [20]. The weights are continuously modified until the neural network is capable of predicting the outputs within an acceptable user-defined error level.

A multiple input neuron model is shown in Figure 3.1, which consists of a single neuron with x_n inputs. A constant “1” is introduced to the neuron as an input and is multiplied by the bias, b.

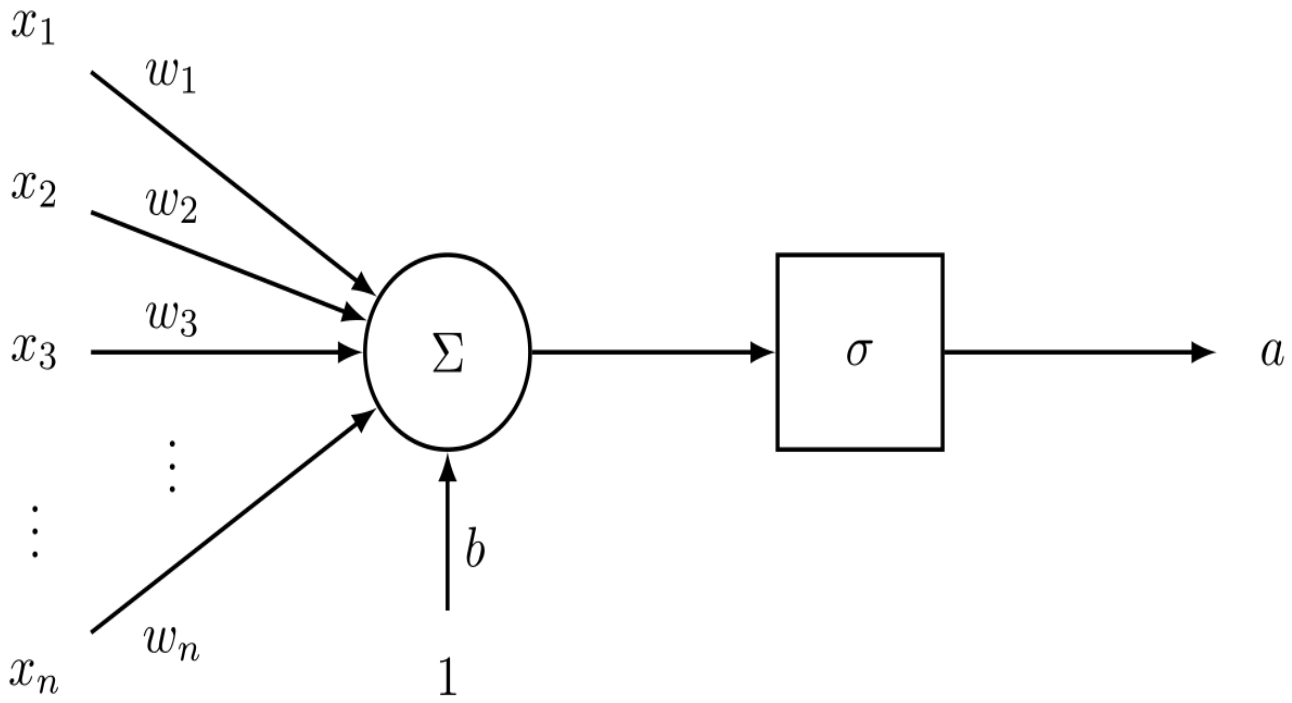

Figure 3.1 Multiple input neuron model

Hence, the net input to the transfer function (f) is defined as the sum of the bias and the weighted inputs, such that:

net_input = $\sum_{n=1}^{n} WnXn$ + b (1)

Where n represents the total number of input variables, x_n shows input and w_n represents synaptic weight. The output for the neuron is computed using the transfer function, such that

Output= f (net_input)

Another neural network architecture is given showing the input nodes or input processing elements in figure 3.2

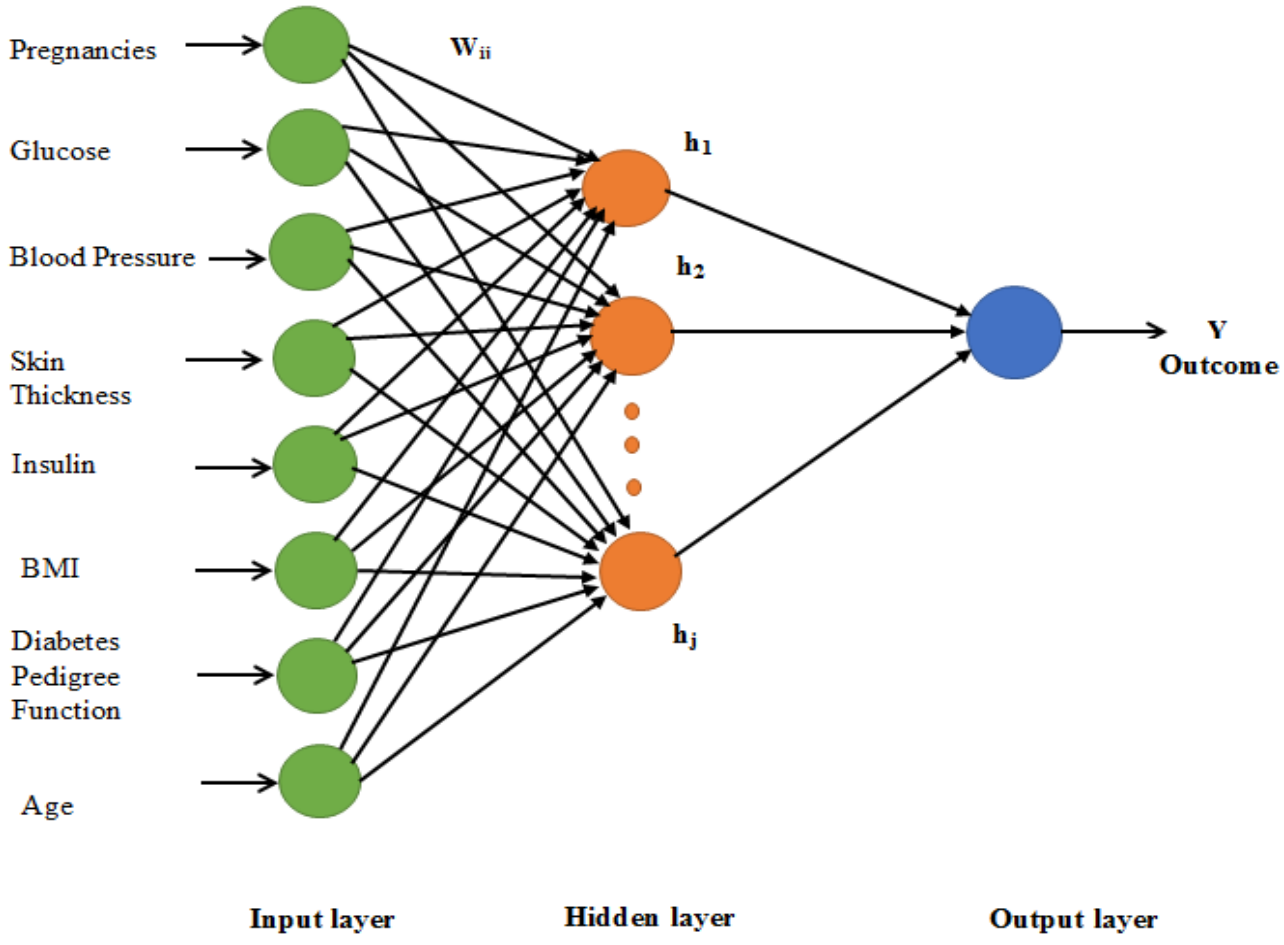

Figure 3.2 Architecture of a simple neural network with one hidden layer

From the figure 3.2 it is shown that the input layer is composed of eight input processing elements or nodes labeled as pregnancies, glucose, blood pressure, skin thickness, insulin, BMI, diabetes pedigree function and age. They are the input parameters of this study which is trained and tested. There is one hidden layer (h_1 ….. h_j). Weight is labeled as w_{ij}. The outcome Y is considered as computed output.

The different architecture of neural network is possible varying different parameters. They are discussed below.

Learning rule or learning process is a method or a mathematical logic which improves the artificial neural network's performance and usually this rule is applied repeatedly over the network. It is done by updating the weights and bias levels of a network when a network is simulated in a specific

data environment. A learning rule may accept existing condition (weights and bias) of the network and will compare the expected result and actual result of the network to give new and improved values for weights and bias. The learning rule is one of the factors which decides how fast or how accurate the artificial network can be developed. There are several learning rules like momentum, step, ConjugateGradient, DeltaBarDelta. This research uses momentum learning rule. Momentum factor is the weight change in a direction that is a combination of current gradient and the previous gradient.

Bias, a bias value allows to shift the activation function to the left or right, which may be critical for successful learning. Bias is much like the weight except that it has a constant input +1.

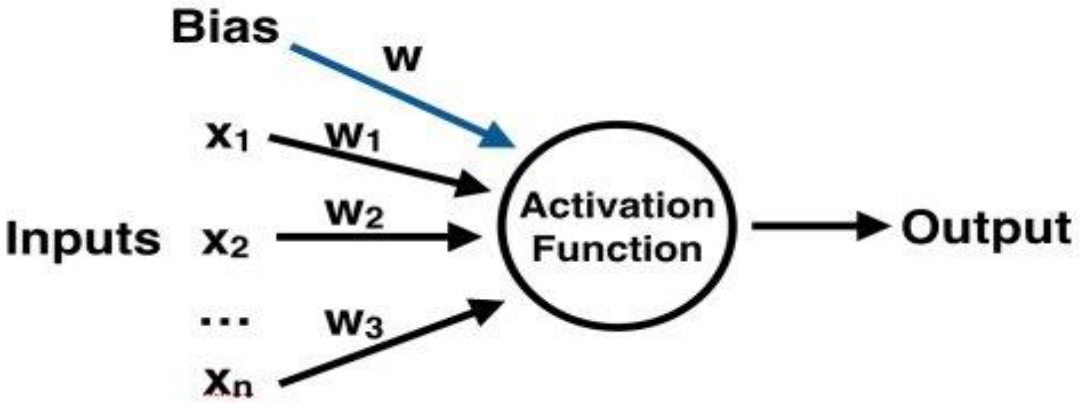

Figure 3.3 Function of bias neuron

Activation function or transfer function in computational networks, the activation function of a node defines the output of that node given an input or set of inputs. In most cases a non-linear activation function is used in order to achieve the advantage of multilayer nets compared with the limited capabilities of single layer nets non-linear function required. Sigmoid function or S-shaped curve is useful activation function. There are two types of sigmoid function.

1. Binary sigmoid, which has a range of (0, 1)

   $f(x) = \frac{1}{1+e^{-x}}$ (2)

2. Bipolar sigmoid, which has a range of (-1, 1)

   $f(\frac{x}{2}) = \frac{1-e^{-x}}{1+e^{-x}}$ (3)

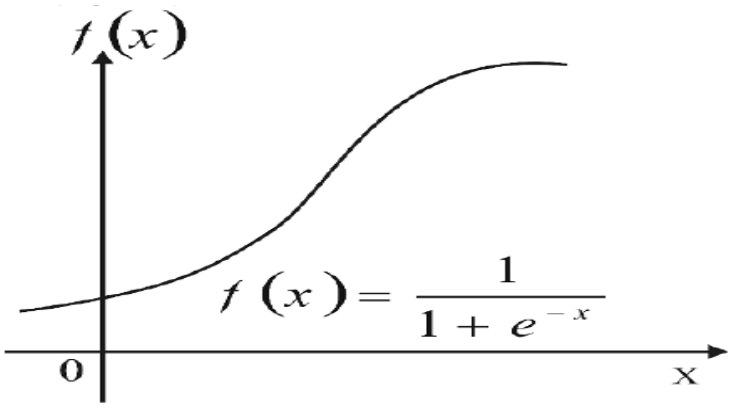

Figure 3.4 Activation function

Learning rate, α controls how radically weights are altered. The learning rate is used to control the amount of adjustment at each step of training.

Epoch is a measure of the number of times all of the training vectors are used once to update the weights. For batch training all of the training samples pass through the learning algorithm simultaneously in one epoch before weights are updated.

Detecting or classifying the Gestational Diabetes Mellitus (GDM) by using artificial neural network (ANN) model can be done by applying different ANN structures to the specific dataset. There are various ANN structures like Multilayer Perceptron Neural Network (MLPNN), Radial Basis Function Neural Network (RBFNN), Self-Organizing Feature Map Network, Recurrent Network, CANFIS Network (Fuzzy logic) and Support Vector Machine. Some or all of the ANN structures can be applied for a specific task to get better result which will provide more accurate result than the others. The network structures and their configuration for this study are discussed below.

3.2 Diagram of proposed methodology

This research of detecting Gestational diabetes Mellitus (GDM) is summarized by the following figure 3.5 given below. It starts with the collection of data like collection of the patient detail. The data of the patients is then is analyzed. Data should be normalized so that we can get better result. Then the input parameters should be normalized. After preparing the training dataset the different artificial neural network will be applied. This study uses six neural network structures. The

obtained result from them is then compared. The network that gives the more accurate result will be chosen. And GDM detection with the selected network configuration will be accomplished.

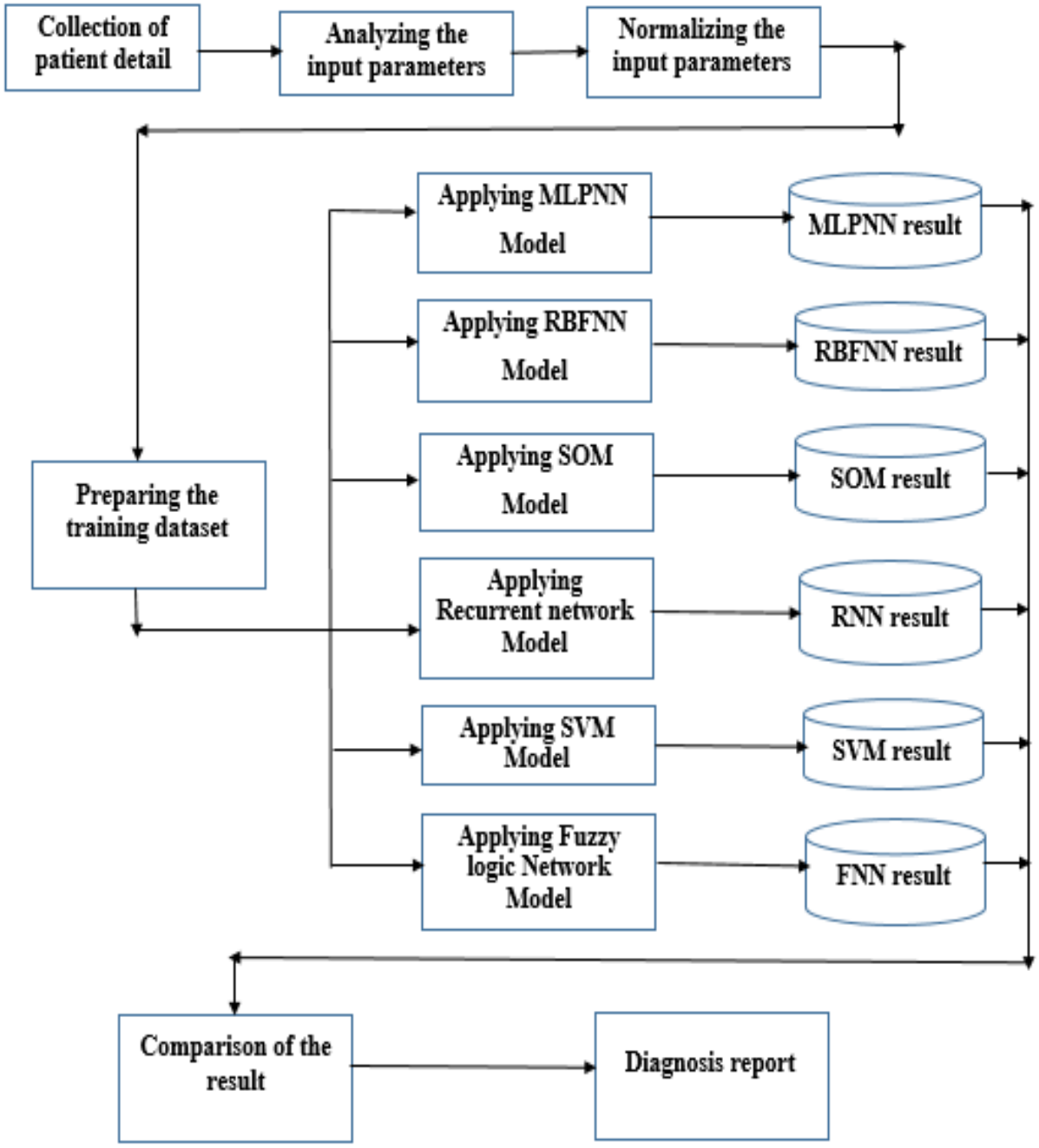

Figure 3.5 Schematic diagram of proposed methodology

3.3 Description of Neural Network Structures

3.3.1 Multilayer Perceptron Neural Network (MLPNN)

The multilayer perceptron (MPL) is one of the most common neural network architecture and has been used successfully in various applications. The MPL network is the most extensively used type of neural network. Multilayer perceptron (MLP) are layered feed-forward networks typically trained with static back-propagation. These networks have found their way into countless applications requiring static pattern classification. Their main advantage is that they are easy to use, and that they can approximate any input/output map. The models are made up of multiple layers of nodes in a directed graph and each of the layers are connected with the adjacent one, hence the name multilayer perceptron. Multilayer perceptron are generally made up of three or more layers. These may consist of an input layer, output layer and one or more hidden layers. They are considered deep neural networks because each layer contains non-linearly activating nodes. Basically the nodes of one layer connect with a specific weight to the nodes of the next layer. The multilayer perceptron uses back-propagation method. Back-propagation is simply a generalization of the least mean squares algorithm in linear perceptron. This is a supervised learning technique where learning occurs by changing connection weights after data is processed. Data processing is done based on the amount of errors in the output compared to the expected results.

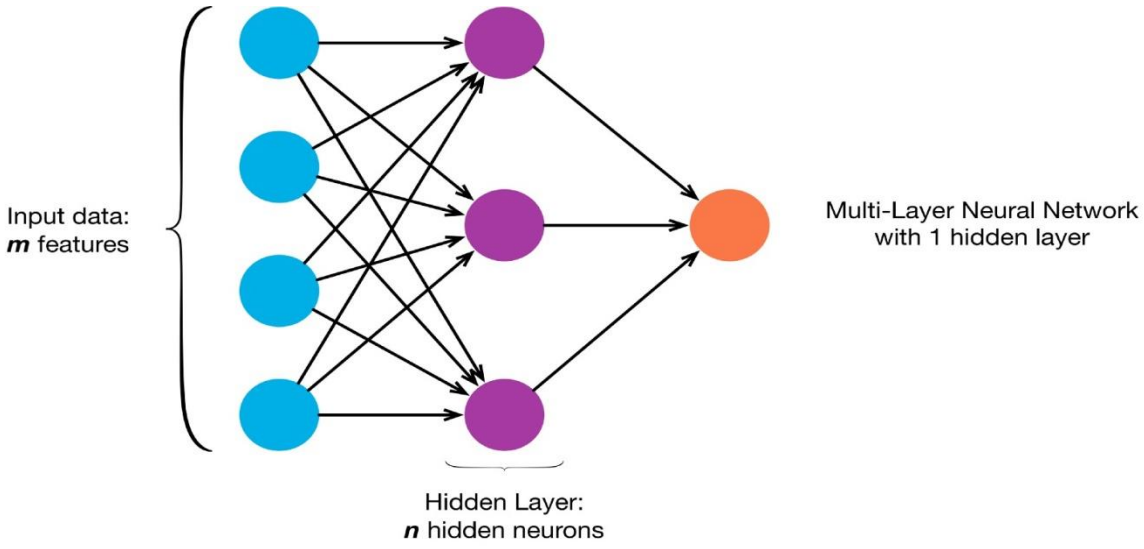

Figure 3.6 Multilayer perceptron neural network architecture with one hidden layer

MLP neural network architecture with one hidden layer is shown in fig 3.6. In this network structure, there are four nodes in the input layer, n nodes in the hidden layer, and one node in the output layer. Thus, the network structure can be defined as 4-n-1.

For detecting GDM using multilayer perceptron neural network (MLPNN) this study uses the following network configuration.

Hidden layer = 1, Processing elements = 7, Epoch number = 20000, Activation function = SigmoidAxon, Learning Rule = Momentum, Time of runs = 3 times, Threshold = .000001.

3.3.2 Radial Basis Function Neural Network (RBFNN)

Radial basis function (RBF) networks are nonlinear hybrid networks typically containing a single hidden layer of processing elements. This layer uses Gaussian transfer functions, rather than the standard sigmoidal functions employed by MLPs. The centers and widths of the Gaussian's are set by unsupervised learning rules, and supervised learning is applied to the output layer. These networks tend to learn much faster than MLPs. Radial basis function neural network (RBFNN) typically have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer. The input can be modeled as a vector of real numbers. The output of the network is then a scalar function of the input vector. An input vector is used as input to all radial basis functions, each with different parameters. The output of the network is a linear combination of the outputs from radial basis functions or units.

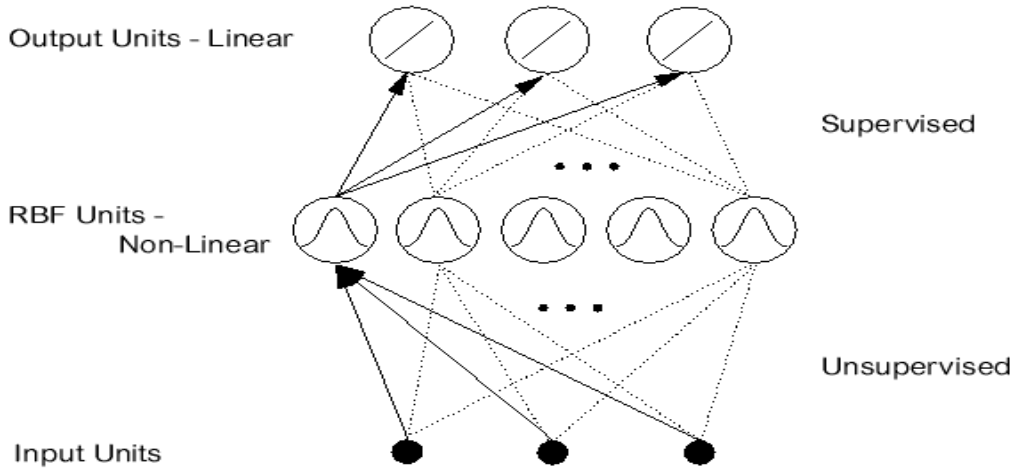

Figure 3.7 Architecture of Radial Basis Function neural network (RBFNN)

For detecting GDM using Radial Basis Function neural network (RBFNN) this study uses the following network configuration. Hidden layer = 1, Processing elements = 5, Epoch number for unsupervised learning = 10000, Epoch number for supervised learning = 20000, Activation function = SigmoidAxon, Learning Rule = Momentum.

3.3.3 Self-Organizing Feature Map (SOM) Neural Network

Self-organizing feature maps (SOM) transforms the input of arbitrary dimension into a one or two dimensional discrete map subject to a topological (neighborhood preserving) constraint. The feature maps are computed using Kohonen unsupervised learning. The output of the SOM can be used as input to a supervised classification neural network such as the MLP. This network's key advantage is the clustering produced by the SOM which reduces the input space into representative features using a self-organizing process. Hence the underlying structure of the input space is kept, while the dimensionality of the space is reduced.

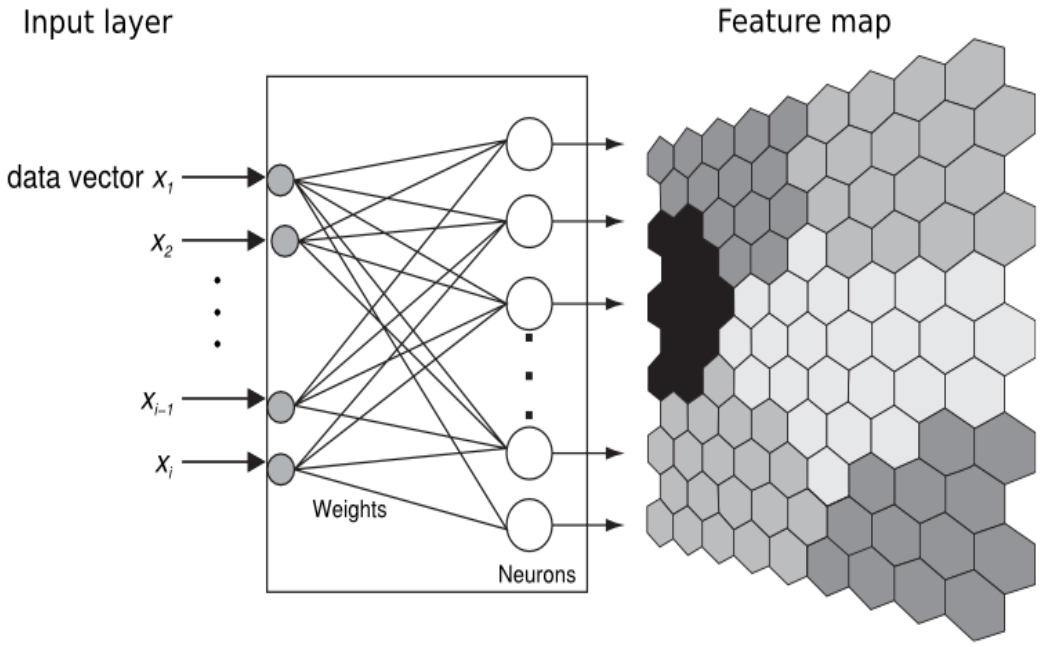

Figure 3.8 Self-Organizing Feature Map (SOM) neural network architecture

For detecting GDM using the network structure by using the Self-organizing feature map for this study uses two hidden layer one with seven processing element and 30000 epoch and the other with five processing element and 30000 epoch, Activation function SigmoidAxon and Learning Rule Momentum factor.

3.3.4 Recurrent Network

A recurrent neural network (RNN) is a class of artificial neural network where connections between nodes form a directed graph along a sequence. This allows it to exhibit dynamic temporal behavior for a time sequence. Unlike feed-forward neural networks, RNNs can use their internal state (memory) to process sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition. Fully recurrent networks feed-back the hidden layer to itself. Partially recurrent networks start with a fully recurrent net and add a feed-forward connection that bypasses the recurrence, effectively treating the recurrent part as a state memory.

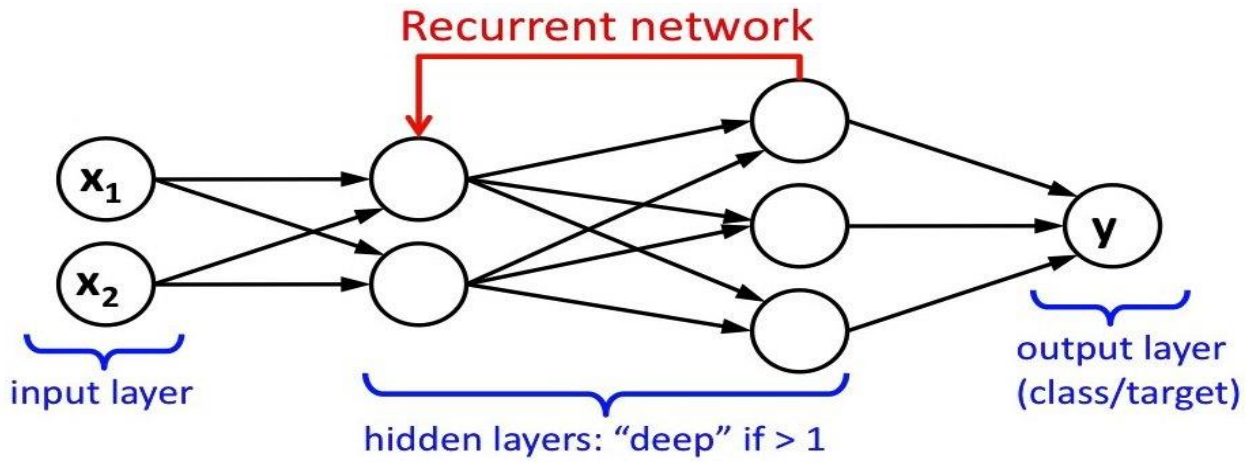

Figure 3.9 Recurrent neural network architecture

For detecting GDM using the network structure by using the recurrent neural network for this study uses one hidden layer with five processing element and 50000 epoch. The activation function is SigmoidAxon and Learning Rule is Momentum factor.

3.3.5 Support Vector Machine (SVM) Neural Network

Support vector machine (SVM) is a relatively new form of supervised machine learning. The Support Vector Machine is implemented using the kernel Adatron algorithm. The kernel Adatron maps inputs to a high-dimensional feature space, and then optimally separates data into their respective classes by isolating those inputs which fall close to the data boundaries. Therefore, the kernel Adatron is especially effective in separating sets of data which share complex boundaries. SVMs can only be used for classification, not for function approximation.

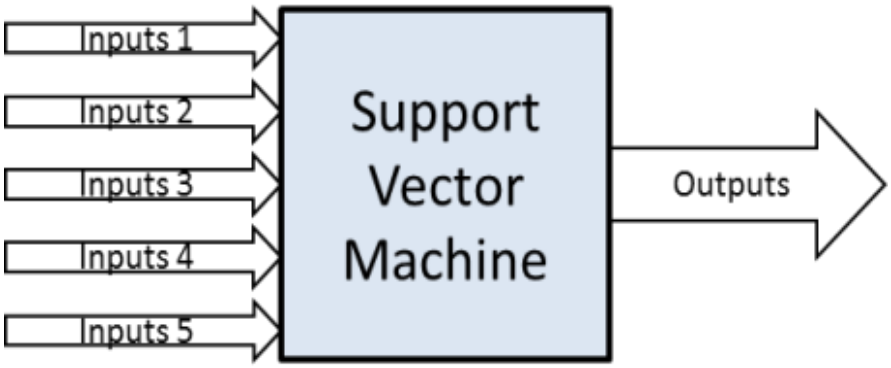

Figure 3.10 Support vector machine neural network architecture

For detecting GDM using the network structure by using the support vector machine (SVM) neural network for this study uses zero hidden layer with one processing element and 10000 epoch. The activation function and Learning Rule is same as the others that is SigmoidAxon and Momentum factor.

3.3.6 CANFIS Network (Fuzzy Logic)

The CANFIS (Co-Active Neuro-Fuzzy Inference System) model combines two approaches, ANN and FL which integrates adaptable fuzzy inputs with a modular neural network to rapidly and accurately approximate complex functions. Fuzzy inference systems are also valuable as they combine the explanatory nature of rules (membership functions) with the power of "black box" neural networks.

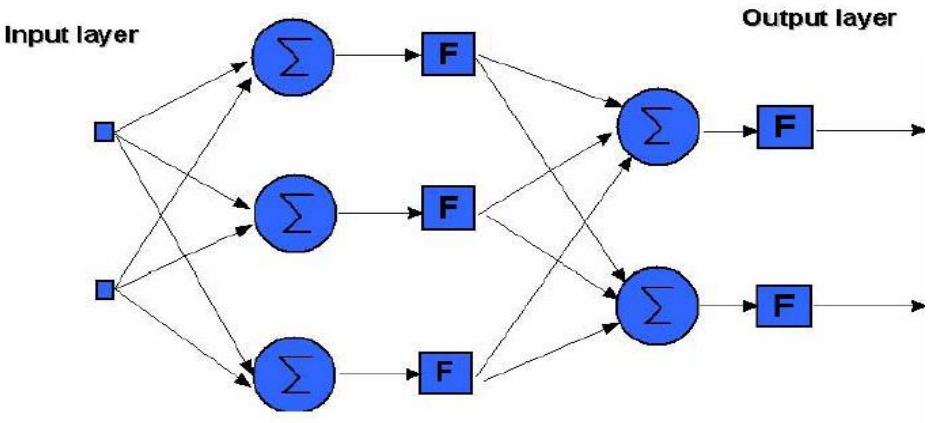

Figure 3.11 Architecture of Fuzzy neural network

For detecting GDM using the network structure by using the fuzzy logic network for this study uses 20000 epoch. The activation function and Learning Rule is same as the others that is SigmoidAxon and Momentum factor.

3.4 Comparing parameters

Applying different artificial neural network structure for any specific study we can get different result. But we have to find the best network structure considering different parameters like Mean Squared Error (MSE), Minimum Absolute Error (MAE), Maximum Absolute Error and Linear Correlation Coefficient (r).

3.4.1 Mean Square Error (MSE)

In neural network, the mean squared error (MSE) or mean squared deviation (MSD) of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors—that is, the average squared difference between the estimated values and what is estimated. With the MSE performance function some other performance functions such as Mean absolute error (MAE), Root Mean Squared Error (RMSE) will be used. The MSE and RMSE will be obtained by Eq. (1) and Eq. (2), respectively.

$$\text{MSE} = 1/\text{N} \sum_{o=1}^{N} (t_T - y_o)^2 \quad (4)$$

$$\text{RMSE} = \sqrt{1/\text{N} \sum_{o=1}^{N} (t_T - y_o)^2} \quad (5)$$

Where, N is the total number of training pattern.

3.4.2 Mean Absolute Error (MAE)

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It's the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight. The MAE can be obtained by Eq. (3), respectively,

$$\text{MAE} = 1/\text{n} \sum_{j=1}^{n} |y_j - \hat{y}_j| \quad (6)$$

3.4.3 Min Absolute Error and Max Absolute Error

Min Abs Error and Max Abs Error can be calculated by the following equations respectively,

Min Abs Error = min $|y_i - t_j|$ (7)

Max Abs Error = max $|y_i - t_j|$ (8)

Where, y_i is desired output, t_j is computed output

3.4.4 Normalized Mean Square Error (NMSE)

The NMSE (Normalized Mean Square Error) is an estimator of the overall deviations between predicted and measured values. It is defined as:

$NMSE = RMSE / (y_{max} - y_{min})$ (9)

NMSE generally shows the most striking differences among models. If a model has a very low NMSE, then it is well performing both in space and time. On the other hand, high NMSE values do not necessarily mean that a model is completely wrong.

3.4.5 Linear correlation coefficient, r

R value, the coefficient of correlation or determination are used to measure the correlation between actual and predicted value. It measures the direction and strength of the linear relationship between actual and predicted value. The r value is always between -1and +1.The highest value of r is 1. The r value is a measure of how well the variation in the output is explained by the target. There is perfect correlation between target and output when this value is equal to 1. A positive r indicates a positive relationship and a negative r indicates a negative relationship.

3.5 Normalization

Normalization is required so that all the inputs are at a comparable range. Because in input layer the multiplied value of weight and input variable should activate to very small less than 3 so it is necessary to get better result it should be normalized. Normalization (or scaling) is one of the main parts of ANN learning process. Normalization is important in ANNs because real data obtained from experiments and analysis most times are distant from each other. The effect is great because the common activation functions such as sigmoid, hyperbolic, tangent and Gaussian produce result that ranges between [0,1] or [-1,1]. It is important to normalize the values to be in that range. If you we not normalize our inputs between (0,1) or (-1,1) you could not equally distribute importance of each input, thus naturally large values become dominant according to less values

during ANN training. Normalization is the process of reorganizing data in a database so that it meets two basic requirements: (1) There is no redundancy of data (all data is stored in only one place), and (2) data dependencies are logical (all related data items are stored together). Therefore the experimental data are normalized according to Eq. (10) in order to train the neural network effectively. Normalization confirms that the neural network was trained effectively without any particular variable significantly distorting the result.

$$X_N = 2\,\frac{x - x_{min}}{x_{max} - x_{min}} - 1 \qquad (10)$$

where, X_N is the normalized value of the real variable

x is the measured value of the variable

x_{min} is the minimum value of the real variable

x_{max} is the maximum value of the real variable

3.6 Training

Once a network has been structured for a particular study, that network is ready to be trained. To start this process the initial weights are chosen randomly. There are two approaches to training - supervised and unsupervised. Supervised training involves a mechanism of providing the network with the desired output either by manually "grading" the network's performance or by providing the desired outputs with the inputs. Unsupervised training is where the network has to make sense of the inputs without outside help. Unsupervised training is used to perform some initial characterization on inputs. In supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. The set of data which enables the training is called the "training set." During the training of a network the same set of data is processed many times as the connection weights are ever refined. The other type of training is called unsupervised training. In unsupervised training, the network is provided with inputs but not with desired outputs. The system itself must then decide what features it will use to group the input data. This is often referred to as self-organization or adaption. The study of detecting Gestational Diabetes Mellitus (GDM) used 60% of total dataset for training approach.

3.7 Testing

Testing of the data is used to confirm the expected result, i.e. when test data is entered the expected result should come and some test data is used to verify the software behavior to invalid input data. Test data is generated by testers or by automation tools which support testing. Data validation is intended to provide certain well-defined guarantees for fitness, accuracy, and consistency for any of various kinds of user input into an application or automated system. This study uses 33% of total dataset for the testing purpose.

3.8 Validation

Data validation is the process of ensuring data have undergone data cleansing to ensure they have data quality, that is, that they are both correct and useful. It uses routines, often called "validation rules" "validation constraints" or "check routines", that check for correctness, meaningfulness, and security of data that are input to the system. The rules may be implemented through the automated facilities of a data dictionary or by the inclusion of explicit application program validation logic. This study uses 7% data from the dataset.

3.9 Dataset description

3.9.1 Background

Gestational Diabetes Mellitus (GDM) can occur in every pregnant women. However, women who have close relatives with the disease are somewhat more likely to develop it. Other risk factors include obesity, high cholesterol, high blood pressure and physical inactivity. The risk of developing GDM also increases, as women take baby at an older age. Women who have overweight are more likely to develop GDM. Women who develop diabetes while pregnant are more likely to develop full-blown diabetes later in life. Poorly managed diabetes can lead to a host of long-term complications among these are heart attacks, strokes, blindness, kidney failure, blood vessel disease.

3.9.2 Dataset

The data used for the model is Pima Indian Diabetes Dataset (PIDD) available https://www.kaggle.com/johndasilva/diabetes/version/1. PIDD includes the following attributes (1-8 attributes as input and last attribute as target variable) number of times pregnant, Plasma glucose concentration a 2 hours in an oral glucose tolerance test, Diastolic blood pressure (mm

Hg), Triceps skin fold thickness (mm), 2-Hour serum insulin (mu U/ml), Body mass index (weight in kg/ (height in m)^2), Diabetes pedigree function and Age (years).

Class to be predicted is patient is tested-positive or tested-negative. A total of 768 cases are available in PIDD. 5 patients had a glucose of 0, 11 patients had a body mass index of 0, 28 others had a diastolic blood pressure of 0, 192 others had skin fold thickness readings of 0, and 140 others had serum insulin levels of 0. After deleting these cases there were 392 cases with no missing values (130 tested positive cases and 262 tested negative).

CHAPTER 4

RESULT AND DISCUSSIONS

This research presents a novel approach to predict gestational diabetes mellitus (GDM). It presents a comparative study conducted on some pregnant women's based on artificial neural network (ANN) models like Multilayer perceptron, Radial Basis Function, Self-Organizing Feature Map, Recurrent Network, Support Vector Machine and Fuzzy logic. Among them the Radial Basis Function Neural network (RBFNN) shows the most promising result.

4.1 Multilayer perceptron neural network (MLPNN)

4.1.1 Training result

The training results of the multilayer perceptron neural network with a specific network configuration are shown below.

Table 4.1 is showing the training result of all the runs of multilayer perceptron neural network with a training minimum value and training standard deviation that gives the value of average of minimum MSE and average of final MSE.

Table 4.1 Training result of MLPNN

All Runs	Training Minimum	Training Standard Deviation
Average of Minimum MSEs	0.0281688927226686	0.0068118759260633
Average of Final MSEs	0.0281688927226919	0.0068118759260467

Table 4.2 is showing the training result of the best network among all network configurations with their run no, epoch no, minimum MSE and final MSE.

Table 4.2 Training result of the best MLP neural network

Best Network	**Training**
Run	2
Epoch	19991
Minimum MSE	0.0235771022072017
Final MSE	0.0235771022072026

Figure 4.1 is showing graphical view of the convergence of average MSE with respect to epoch no. The solid line is showing the average MSE with respect to epoch of training and the dashed line is for the standard deviation.

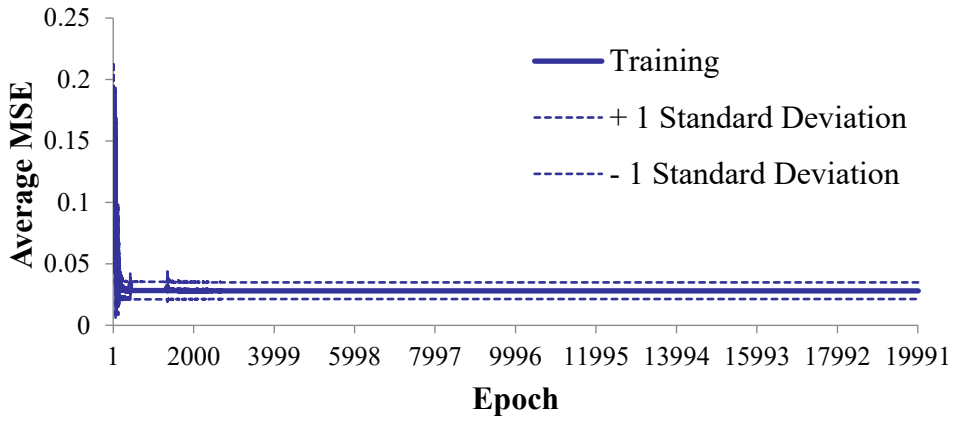

Figure 4.1 Convergence of Avg training MSE with respect to number of iteration or epoch

Figure 4.2 is showing graphical view of the Convergence of MSE with respect to number of iteration or epoch. Here MSE is calculated by Run1, 2 and 3.

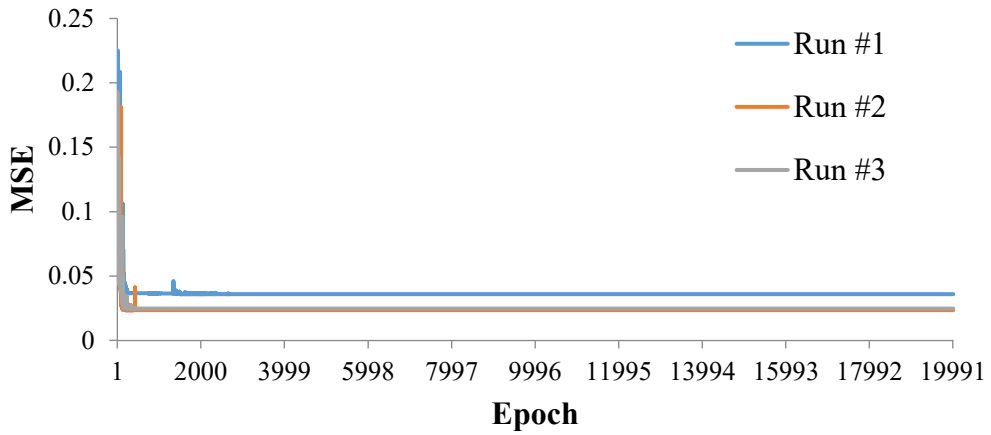

Figure 4.2 Convergence of MSE with respect to number of iteration or epoch

4.1.2 Testing result

The testing result of the built network configuration with computed and desired output number is showing on the Table 4.3 Here the outcome of 0's and 1's is given by the matrix form.

Table 4.3 Testing result of desired output (0) and output (1) of MLPNN

Output / Desired	Outcome(0)	Outcome(1)
Outcome(0)	57	15
Outcome(1)	125	57

Table 4.4 shows the result of testing performance parameters like mean square error (MSE), normalized mean square error (NMSE), mean average error, min absolute error, max absolute error, linear correlation coefficient (r) and percent of correct output values. Linear correlation coefficient (r) is used to measure the performance of neural network model in testing with their outcome's.

Table 4.4 Testing result showing the performance and outcome of MLPNN

Performance	Outcome(0)	Outcome(1)
MSE	0.254838194	0.24088323
NMSE	0.404754398	0.304754398
MAE	0.504754398	0.490712546
Min Abs Error	0.487110916	0.46964414
Max Abs Error	0.527091662	0.512081184
r	.53200	.50012
Percent Correct	31.31868132	79.16666667

4.1.3 Validation result

Validation result of a network structure proves the validity of a research. By using the MLP neural network this study has achieved only 64% accuracy. In the fig there is the comparison of desired and computed neural network output.

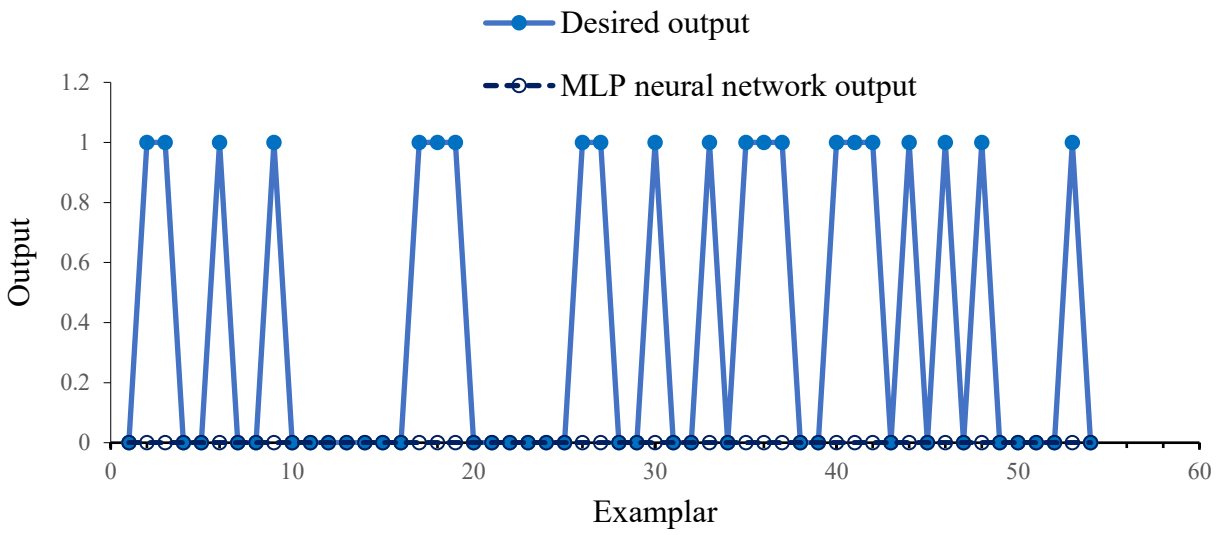

Figure 4.3 Desired vs. Computed MLP neural network output

4.2 Radial basis function neural network (RBFNN)

The radial basis function neural network (RBFNN) configuration for this research shows the more accurate result than the other network configuration. The training, testing and validation results are shown by the figures and tables given below.

4.2.1 Training result

The training result of radial basis function neural network structure for the research is shown for the epoch number of 10000.

In the following table the computed minimum mean square (MSE) error and final MSE for the best network configuration structure is given.

Table 4.5 Training result of the best network of RBFNN

Best Network	Training
Epoch	9990
Minimum MSE	0.033558199
Final MSE	0.033598587

In the following fig 4.4 training mean square error vs. epoch is shown for the specific epoch. The solid line is showing the training MSE with respect to the epoch number.

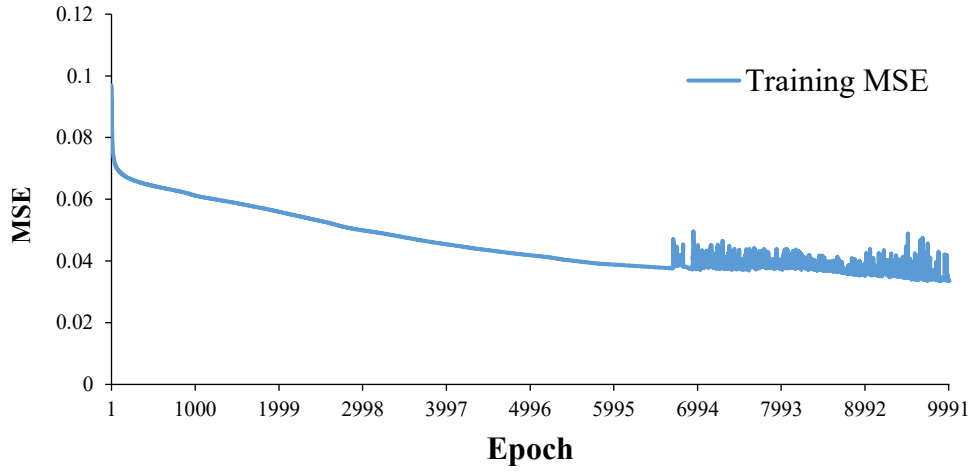

Figure 4.4 Training MSE vs. Epoch

4.2.2 Testing result

The testing result of the Radial Basis Function (RBFNN) is shown by the figure given below. The desired output and actual radial basis function neural network output is shown concurrently.

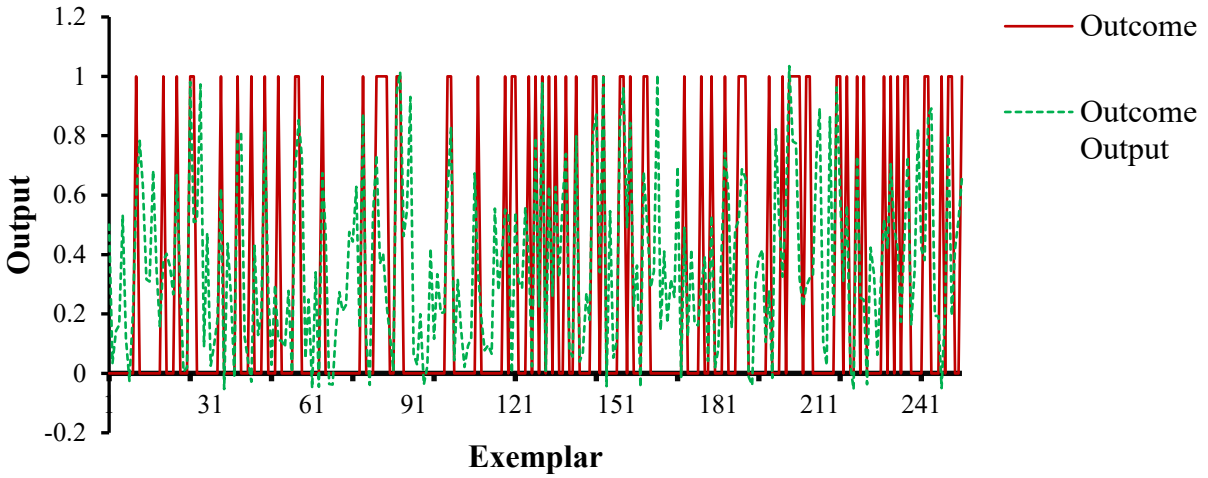

Figure 4.5 Testing graph of desired output and actual output

Table of testing performance parameters like mean square error (MSE), normalized mean square error (NMSE), mean average error, min absolute error, max absolute error, linear correlation coefficient (r) and percent of correct output values and their calculated outcome is given below.

Table 4.6 Testing result with performance and output of RBFNN

Performance	Outcome
MSE	0.159367498
NMSE	0.782761984
MAE	0.31359339
Min Abs Error	0.004629013
Max Abs Error	1.050074899
r	0.71565647

4.2.3 Validation result

Validation result of this study by using Radial Basis Function neural network (RBFNN) has achieved 87.3% accuracy. This figure shows the graphical view in basis of the comparison between the desired output and Radial Basis Function neural network (RBFNN) output.

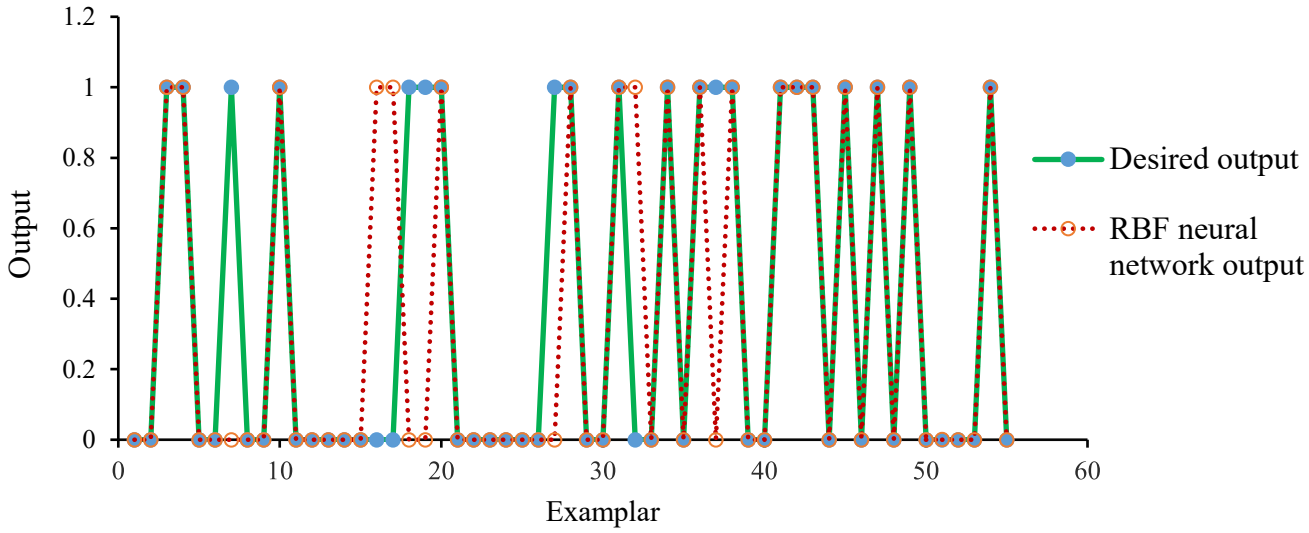

Figure 4.6 Desired vs. Computed RBF neural network output

4.3 Self-organizing feature map (SOM) Neural Network

The network structure by using the Self-organizing feature map for this study uses two hidden layer one with seven processing element and 30000 epoch and the other with five processing element and 30000 epoch. The train, test and validation result is given by the following tables and figures.

4.3.1 Training result

The following table shows the best network configuration of training result with the epoch number, minimum MSE, final MSE.

Table 4.7 Training result of SOM neural network

Best Network	Training
Epoch	2601
Minimum MSE	0.051060059
Final MSE	0.065314239

The graphical view of the training MSE with respect to epoch number by the training is given below.

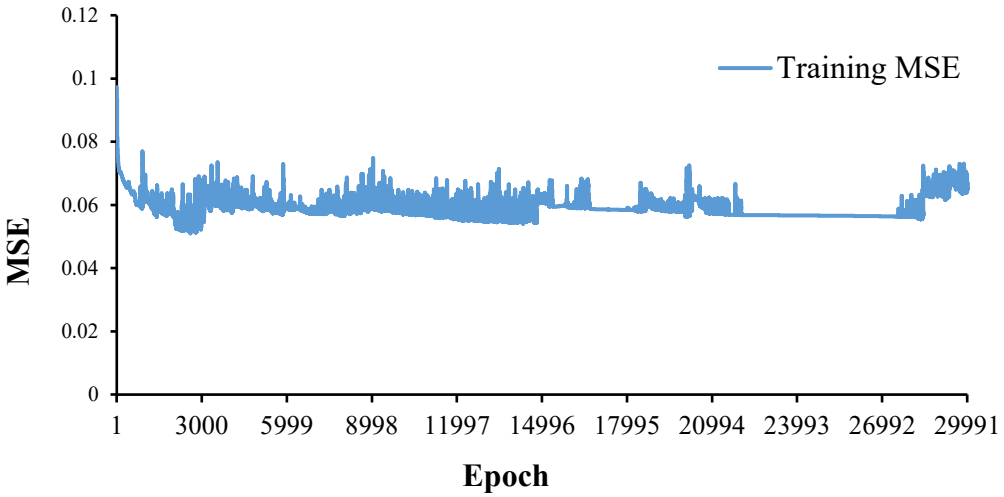

Figure 4.7 Training MSE vs. Epoch

4.3.2 Testing result

The testing result of the Self-organizing feature map neural network is shown by the figure given below. The desired output and actual neural network output is shown concurrently by this graphical view.

This table shows the numerical values of testing performance parameters like MSE, NMSE, MAE, Min Absolute Error, Max Absolute Error and linear correlation coefficient (r) value.

Table 4.8 Testing result with performance parameters and outcomes of SOMNN

Performance	Outcome
MSE	0.173062508
NMSE	0.850027475
MAE	0.349155235
Min Abs Error	0.001765262
Max Abs Error	0.923917657
r	0.504145591

The testing result of the Self-organizing feature map neural network is shown by the figure given below. The desired output and neural network output is shown concurrently.

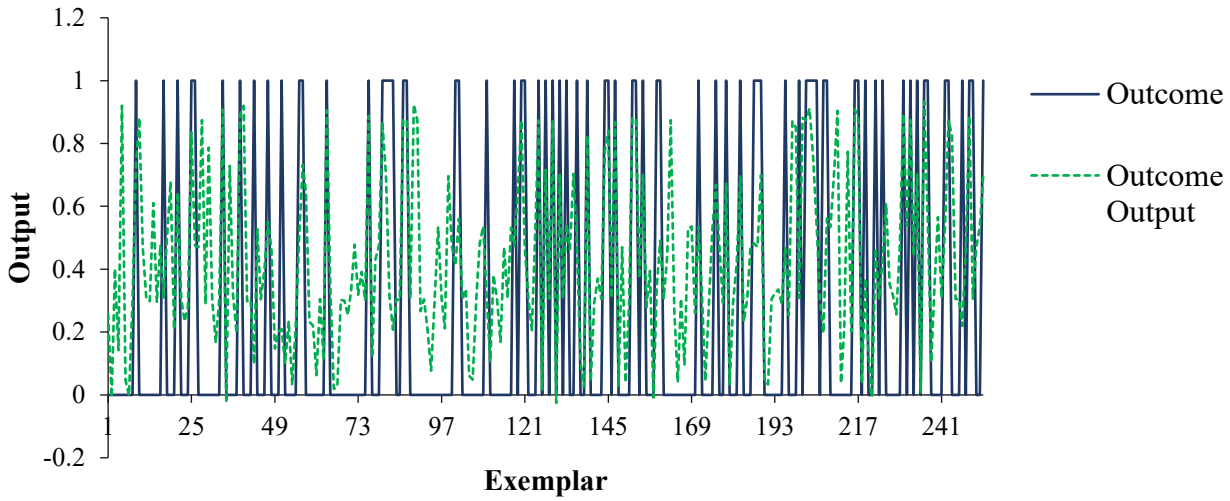

Figure 4.8 Testing output vs. exemplar

4.3.3 Validation result

Validation result of this study by using Self-organizing feature map neural network has achieved 83.64% accuracy. This figure shows the graphical view in basis of the comparison between the desired output and neural network output.

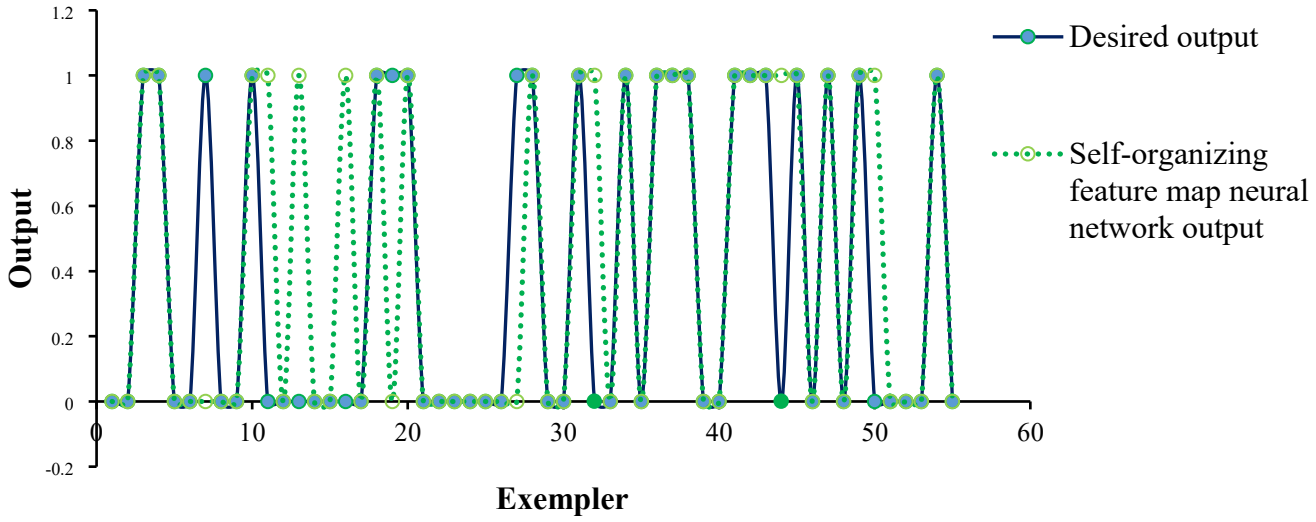

Figure 4.9 Desired vs. Computed neural network output

4.4 Recurrent network

The network structure by using the recurrent network for this study uses one hidden layer with five processing element and 50000 epoch. The train, test and validation result is given by the following tables and figures.

4.4.1 Training result

The following table shows the best network configuration of training result with the epoch number, minimum MSE, final MSE.

Table 4.9 Training result of recurrent neural network

Best Network	Training
Epoch	3315
Minimum MSE	0.065820911
Final MSE	0.067774138

In the following figure training mean square error vs. epoch is shown for the specific epoch. The solid line is showing the training MSE with respect to the epoch number.

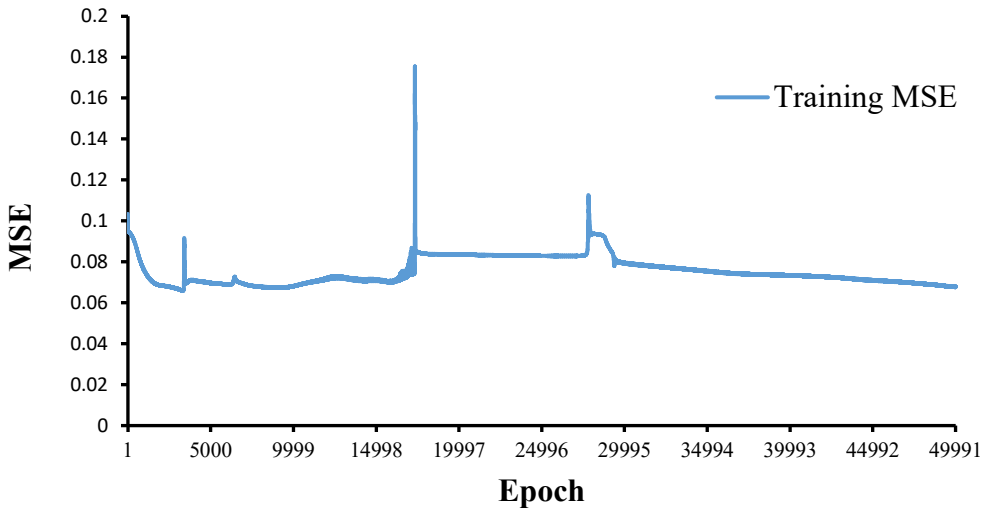

Figure 4.10 Training MSE vs. Epoch of recurrent neural network

4.4.2 Testing result

This table shows the numerical values of testing performance parameters like MSE, NMSE, MAE, Min Absolute Error, Max Absolute Error and linear correlation coefficient (r) value and their outcome's.

Table 4.10 testing result of recurrent neural network

Performance	Outcome
MSE	0.140747968
NMSE	0.691308831
MAE	0.310484452
Min Abs Error	0.000834192
Max Abs Error	0.984280028
r	0.577301842

The testing result of the recurrent neural network is shown by the figure given below. The desired output and actual neural network output is shown concurrently by this graphical view.

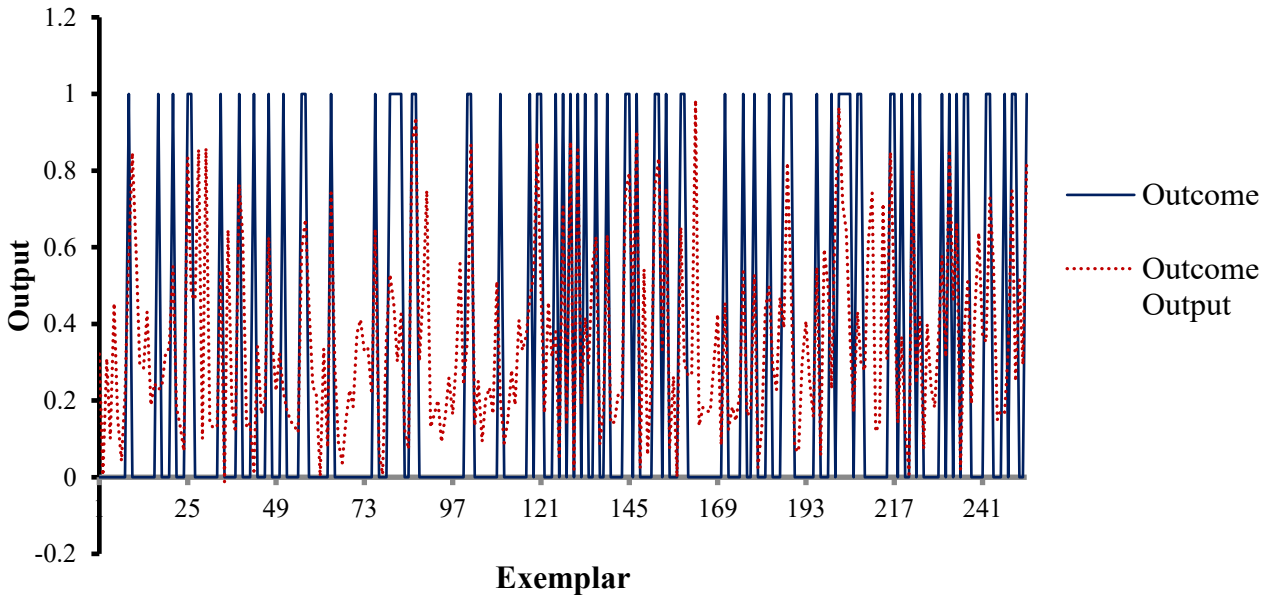

Figure 4.11 Testing output vs. exemplar

4.4.3 Validation result

Validation result of this study by using recurrent neural network has achieved 83.64% accuracy on detecting gestational diabetes. This figure shows the graphical view in basis of the comparison between the desired output and recurrent neural network output.

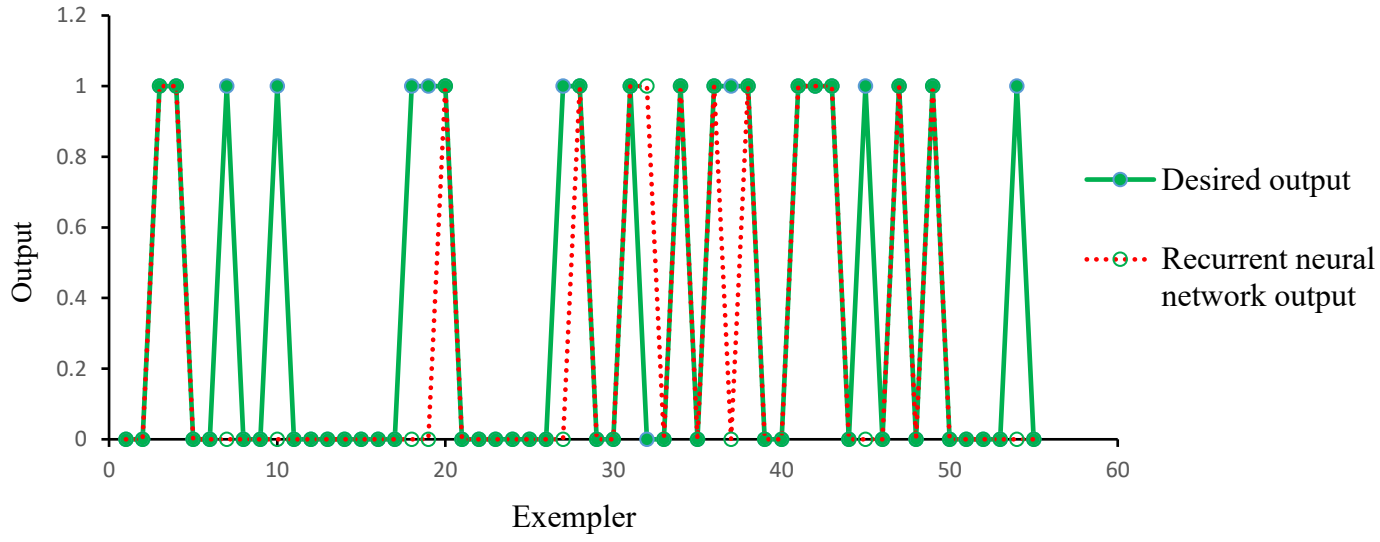

Figure 4.12 Desired vs. Computed recurrent neural network output

4.5 Support vector machine (SVM) neural network

The network structure by using the Support Vector Machine neural network (SVMNN) for this study does not use any hidden layer but with one processing element and 10000 epoch. The train, test and validation result is given by the following tables and figures.

4.5.1 Training result

The following table shows the best network configuration of training result with the epoch number, minimum MSE, final MSE.

Table 4.11 training result of SVM neural network

Best Network	Training
Epoch	10000
Minimum MSE	0.036260495
Final MSE	0.036260495

Training mean square error with respect to the epoch number of the training phase is given by the following figure.

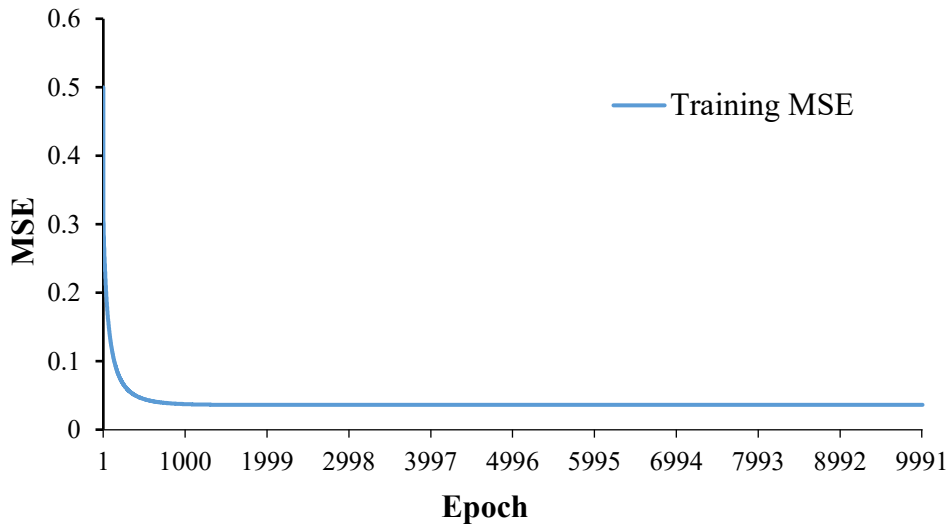

Figure 4.13 Training MSE vs. Epoch of Support Vector Machine neural network (SVMNN)

4.5.2 Testing result

The numerical values of testing performance parameters like MSE, NMSE, MAE, Minimum Absolute Error, Maximum Absolute Error and linear correlation coefficient (r) value and their outcomes are given by the following table.

Table 4.12 Testing result of SVM neural network

Performance	Outcome
MSE	0.210023444
NMSE	1.031567726
MAE	0.366041382
Min Abs Error	0.004239389
Max Abs Error	1.418548728
r	0.427297873

The testing result of the Support Vector machine neural network (SVMNN) is shown by the figure given below. The desired output and actual neural network output is shown concurrently by this graphical view.

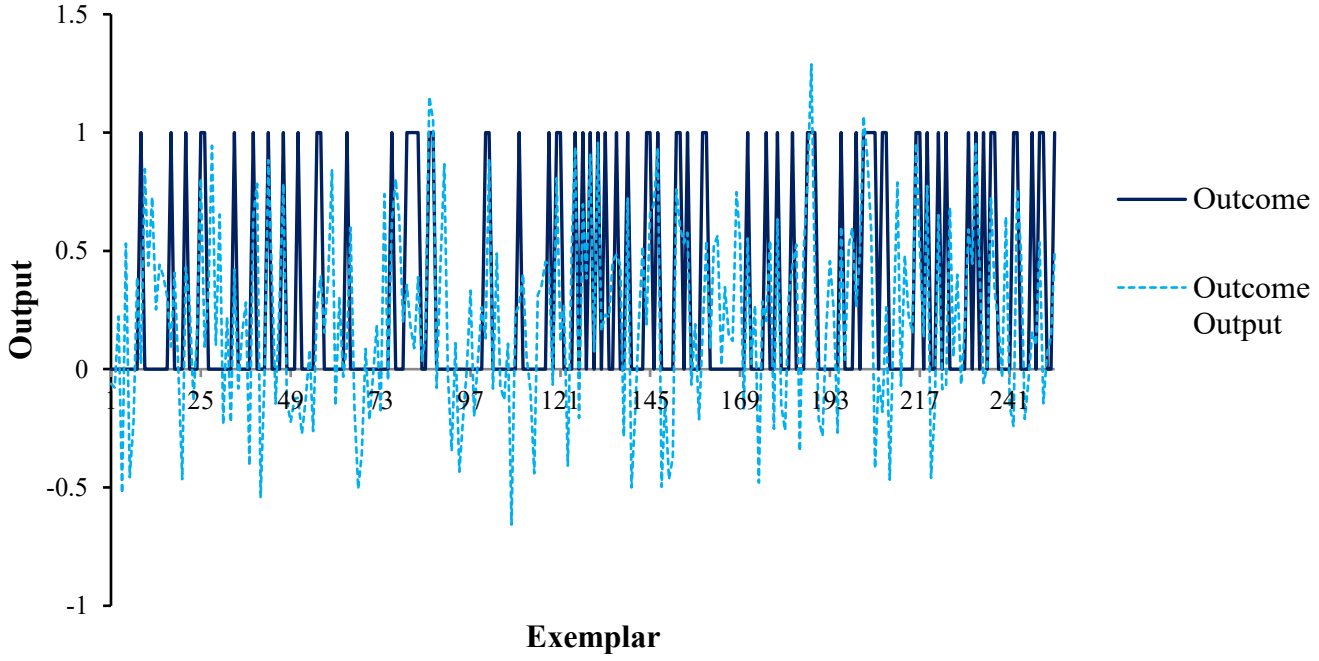

Figure 4.14 Testing output vs. exemplar

4.5.3 Validation result

Validation result of this study by using SVM neural network has achieved only 76.37% accuracy on detecting gestational diabetes. This figure shows the graphical view on basis of the comparison between the desired output and recurrent neural network output.

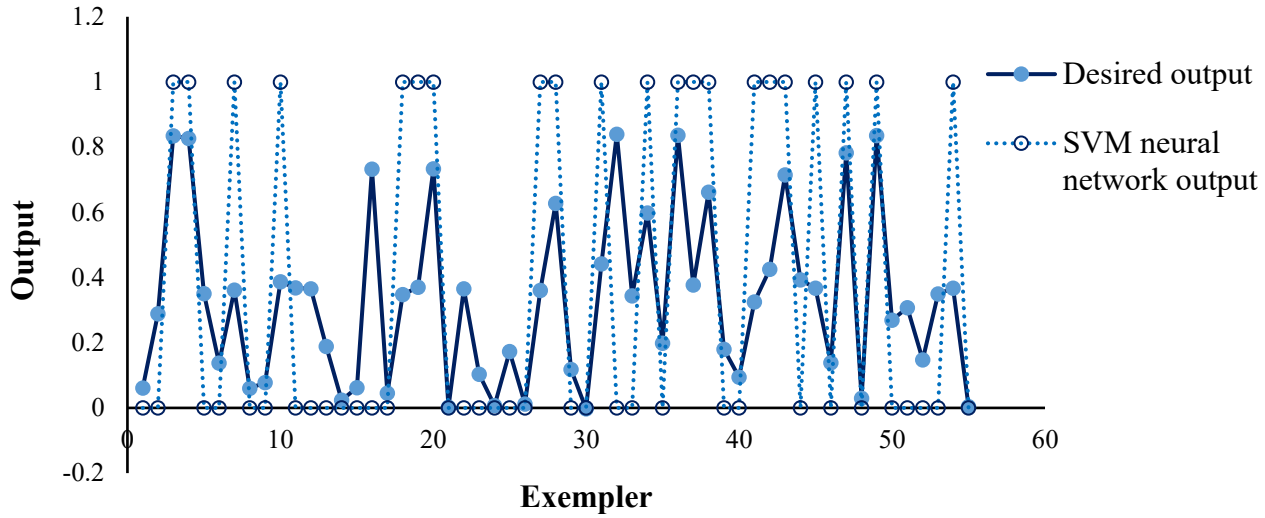

Figure 4.15 Desired vs. Computed recurrent SVM neural network output

4.6 Fuzzy logic network

4.6.1 Training result

The network structure by using the Fuzzy logic neural network for this study use 20000 epoch. The train, test and validation result is given by the following tables and figures.

The following table shows the best network configuration of training result with the epoch number, minimum MSE, final MSE.

Table 4.13 Training result of fuzzy neural network

Best Network	Training
Epoch	14034
Minimum MSE	0.036260495
Final MSE	0.036260495

Training mean square error with respect to the epoch number of the training phase is given by the following figure.

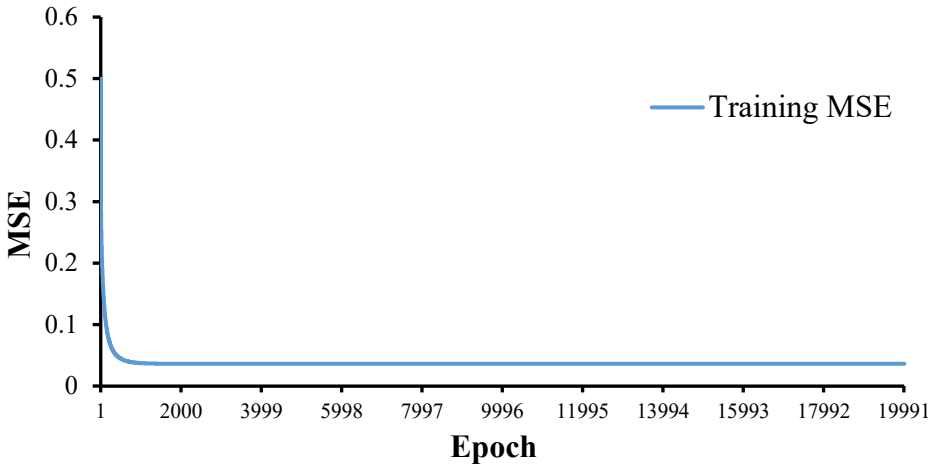

Figure 4.16 Training MSE vs. Epoch of Fuzzy logic neural network

4.6.2 Testing result

The numerical values of testing performance parameters like MSE, NMSE, MAE, Min Absolute Error, Max Absolute Error and linear correlation coefficient (r) value and their outcome's.

Table 4.14 Testing result of fuzzy neural network

Performance	Outcome
MSE	0.210023444
NMSE	1.031567726
MAE	0.366041382
Min Abs Error	0.004239389
Max Abs Error	1.418548728
r	0.427297873

The testing result of the recurrent neural network is shown by the figure given below. The desired output and actual neural network output is shown concurrently by this graphical view.

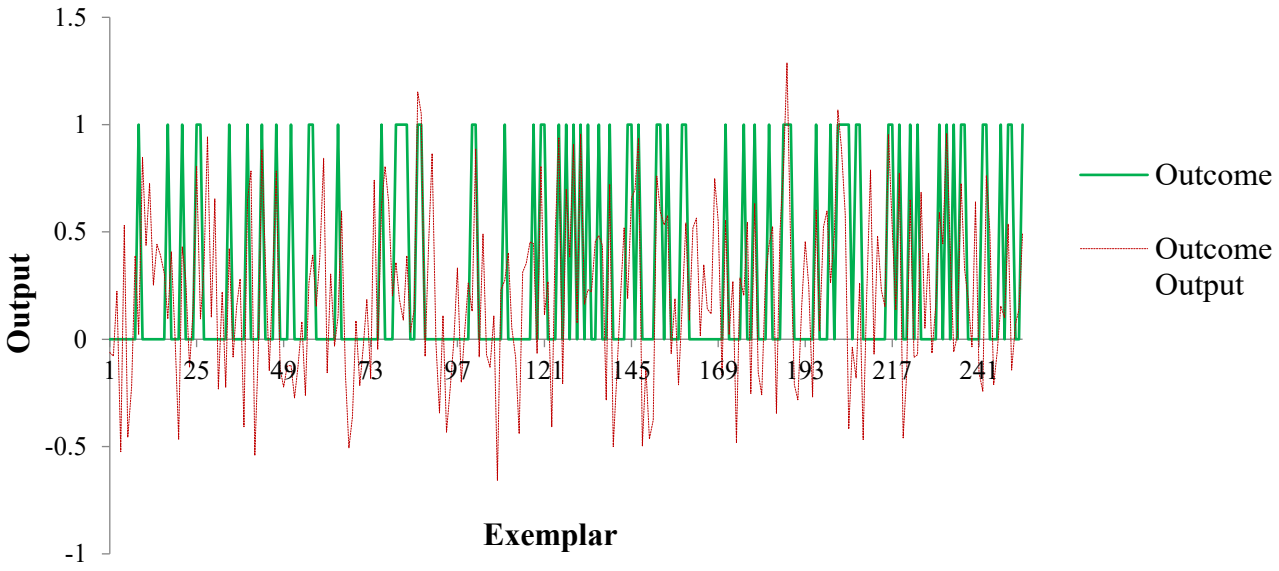

Figure 4.17 Convergence of testing output with respect to exemplar

4.6.3 Validation result

Validation result of this study by using Fuzzy logic neural network has achieved 74.6% accuracy on detecting gestational diabetes. This figure shows the graphical view on basis of the comparison between the desired output and fuzzy logic neural network output.

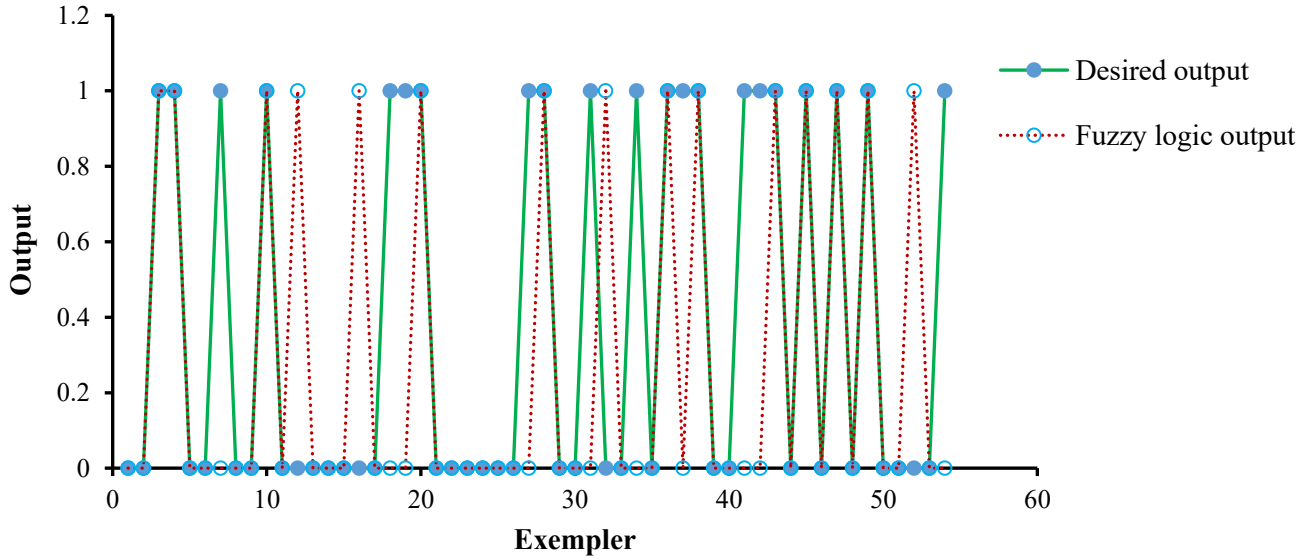

Figure 4.18 Desired vs. Computed recurrent fuzzy neural network output

4.7 Comparison between the neural network structures

The different neural network structures varies with their varying epoch number, processing elements, hidden layer, transfer function, activation function. The result for a specific study varies by altering them and they build different network structures that shows different results. Some neural network structures shows more accurate result than the others. In every research, the best network is chosen considering the parameters like mean square error (MSE), standard deviation, linear correlation coefficient (r) and many others. In this study there is developed such a comparison among the built neural network structure. There is a table showing all the attributes that differs one network from another in this study. Table is showing the parameters and their values.

Table 4.15 Comparison of the neural network structures by training and testing results

Neural network structures	**Training**	**Testing**	
	MSE	MSE	r
Multilayer perceptron	0.0235771022072026	0.254838194	0.532001001
Support Vector machine	0.036260495	0.210023444	0.427297873
Recurrent network	0.067774138	0.140747968	0.577301842
Fuzzy logic	0.036260495	0.210023444	0.427297873
Self-organizing feature map	0.065314239	0.173062508	0.504145591
Radial Basis Function	0.033598587	0.159367498	0.71565647

Different neural network structures show different Mean Square Error (MSE) and linear correlation coefficient (r). The value of MSE for each network structure is kept as low as possible.

On the other hand a network structure is considered to be better than other when its r value is near to 1. From the table of comparison we can see that the multilayer perceptron neural network shows the lowest MSE of 0.0235771022 in training but in testing its increases to 0.254838194. On the other hand the recurrent neural network structure shows the lowest MSE in testing that is 0.140747968.

From validation we get the average percentage of accuracy. Accuracy of a neural network finally decides which network structure will be more reliable for this research. Though the r value of recurrent network is good compared to the other except RBFNN and the MSE of multilayer perceptron is low from other structures, their accuracy is lower than radial basis function neural network (RBFNN) structure. Multilayer perceptron shows only 64% accuracy of detecting gestational diabetes. Where support vector machine neural network shows 76.37%, recurrent network 83.64%, radial basis function neural network (RBFNN) 87.3%, and fuzzy logic network 74.6% and self-organizing feature map shows 83.64% accuracy. The tabular form of the comparison between them is given by the following table.

Table 4.16 Comparison of the neural network structures by validation results

Neural network structure	**Accuracy**
Multilayer perceptron	64%
Support Vector machine	76.37%
Recurrent network	83.64%
Fuzzy logic	74.6%
Self-organizing feature map	83.64%
Radial Basis Function	87.3%

RBFNN shows 87.3% which is near to approximately 88%. From the previous research of detecting gestational diabetes the rate of accuracy obtained by radial basis function neural network is only 82%. So the radial basis function neural network structure for detecting gestational diabetes is much better than other research's. So this research of detecting Gestational Diabetes Mellitus (GDM) selects the network structure of Radial Basis Function Neural Network (RBFNN) as it shows the highest accuracy.

The statistical view of the comparison is shown by the diagram given below.

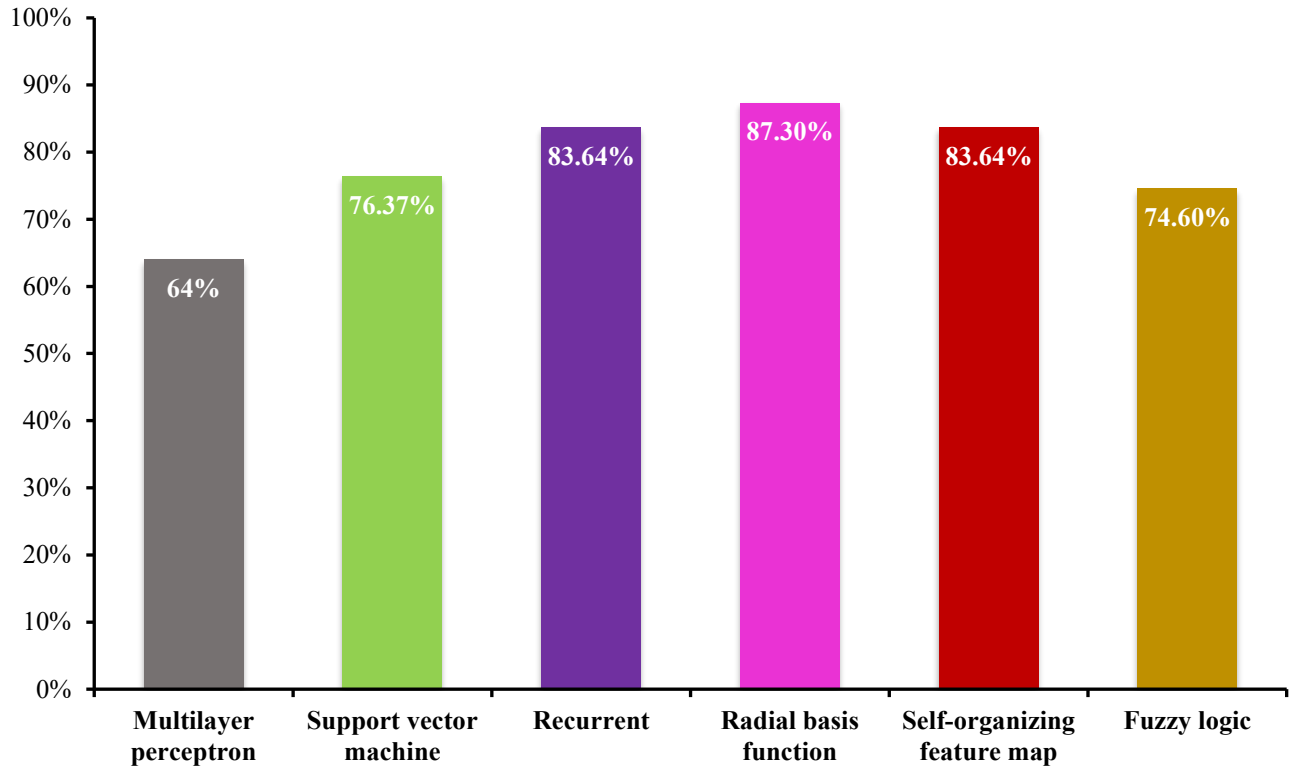

Figure 4.19 Statistical view of the comparison of different neural network structures

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

Gestational diabetes is a disorder of glucose tolerance occurred or first recognized during pregnancy. The excess glucose in the mother is transmitted to the fetus. Gestational Diabetes metabolic disorder is highly prevailing among pregnant women nowadays. Various risk factors are associated with this disorder thus leading to complications to both mother and neonatal. There can be long term risk to both mother and infant if not treated. Therefore, to maintain optimal glycaemic control there is a need to adopt appropriate screening and diagnose method. Even though shortly after delivery glucose tolerance usually returns to normal, there is strong evidence that women with GDM have a high risk for developing diabetes in the course of their lives. As GDM is widely prevalent, many pregnant women have the fear of acquiring it. The risk during pregnancy is less if GDM is diagnosed earlier. Therefore early identification of women at risk of GDM is recommended to prevent complications. The increasing demand of Artificial Neural Network applications for predicting the disease shows better performance in the field of medical decision-making. Considering the great potential of this technique this research aims to build different artificial neural network model to detect GDM and to compare the models for early prediction of women at risk for the development of gestational diabetes mellitus (GDM) and to choose the best network model among them.

5.2 Future Work

Usually only women who have risk factors such as obesity or a family history of GDM are screened earlier on in pregnancy. Therefore, women who develop GDM and do not have these common risk

factors often remain undiagnosed until the second trimester and a delay in diagnosis often means therapies for GDM are less effective. While GDM can often be controlled through proper diet, exercise and medication, early diagnosis and treatment are crucial for women hoping to manage their high blood sugar and prevent complications during their pregnancy. The above research clearly shows that when considering the inputs to the models, there is at least one input value for which the patient should get the help of a doctor or a hospital staff. My future research will propose a system that will help pregnant women in the early stage in diagnosing GDM using newly designed attributes, without even taking a blood test and hence is cost effective. This study offers every pregnant woman the opportunity to know her risk early on without even going to the hospital.

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