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TYPE-2 FUZZY NEURAL SYSTEM FOR DIAGNOSIS OF DIABETES

Ph.D. THESIS

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Approval

We certify that we have read the thesis submitted by Hamit ALTIPARMAK titled **"Type-2 Fuzzy Neural System for Diagnosis of Diabetes**" and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy in Computer Engineering.

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not orginal to this work.

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Abstract

Type-2 Fuzzy Neural System for Diagnosis of Diabetes

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The process of diagnosis of diabetes is complex and requires a high level of expertise. The diabetes is characterized by set of symptoms and signs. These are age, gender, body mass index, fasting sugar, blood pressure, skin fold thickness, insulin level and family history of diabetes. Using these parameters set of techniques are used for designing system diagnosing the diabetes. Sometimes, the determination of intervals of input symptoms affecting the human healthy is very difficult. The doctors may interpret the input signals differently and analyze the intervals for diagnosis of disease differently. Intervals about the health issues are often characterized uncertainty. Also, in many cases the medical data characterizing the input symptoms has a noisy character and characterized uncertainty and imprecision. In such cases one of appropriate methodologies used for diagnosing diabetes is the use of fuzzy sets theory. Several research studies are used for identification of diabetes. Sometimes, the high level of uncertainty in medical data requires the use of type-2 fuzzy set theory in handling these uncertainties.

In this thesis T2FNN (Type-2 Fuzzy Neural Network) model is proposed for the diagnosis of diabetes. The model proposed is the integration of Type-2 Fuzzy Logic and Artificial Neural Networks. The structure of T2FNN system for diagnosis of diabetes has been developed. The design stages of T2FNN model is presented. The design of T2FNN model is based on statistical data. Two diabetes data sets are used for the design of diagnostic system. Simulations were carried out to measure the performance of the created T2FNN architecture. Comparative simulation results, the details of which are given in the thesis, have proven the effectiveness of using our T2FNN architecture in the diagnosis of diabetes.

Keywords: Diabetes, fuzzy logic, artificial neural network, diagnostic system, T2FNN

Özet

Diyabet Teşhisi için Tip-2 Bulanık Sinir Sistemi

Altıparmak, Hamit

Doktora, Bilgisayar Mühendisliği Bölümü

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Diyabet teşhisi süreci karmaşıktır ve yüksek düzeyde uzmanlık gerektirir. Diyabet, bir dizi belirti ve bulgu ile karakterizedir. Bunlar yaş, cinsiyet, vücut kitle indeksi, açlık şekeri, tansiyon, deri kıvrım kalınlığı, insülin düzeyi ve ailede diyabet öyküsüdür. Bu parametreleri kullanarak diyabeti teşhis eden sistem tasarlamak için bir dizi teknik kullanılmaktadır. Bazen insan sağlığını etkileyen girdi belirtilerinin aralıklarının belirlenmesi çok zordur. Gerçek hayatta, giriş sinyallerini farklı aralıklara bölerek ve analiz ederek doktorlar hastalığı teşhis eder. Bu aralıklar genellikle belirsizlikle karakterize edilir. Ayrıca, birçok durumda girdi belirtilerini karakterize eden tıbbi veriler gürültülü bir karaktere sahiptir bu da belirsizlik ve kesinliği karakterize eder. Bu gibi durumlarda diyabet teşhisi için kullanılan uygun metodolojilerden biri bulanık kümeler teorisinin kullanılmasıdır. Bazen, tıbbi verilerdeki yüksek düzeyde belirsizlik, bu belirsizliklerin ele alınmasında tip-2 bulanık küme teorisinin kullanılmasını gerektirir.

Bu tezde diyabet teşhisi için T2FNN (Tip-2 Bulanık Sinir Ağı) modeli önerilmiştir. Önerilen model, Tip-2 Bulanık Mantık ve Yapay Sinir Ağlarının entegrasyonudur. Diyabet teşhisi için T2FNN sisteminin yapısı geliştirilmiştir. T2FNN modelinin tasarım aşamaları sunulmuştur. T2FNN modelinin tasarımı istatistiksel verilere dayanmaktadır. Tanı sisteminin tasarımı için iki diyabet veri seti kullanılmıştır. Oluşturulan T2FNN mimarisinin performansını ölçmek için simülasyonlar yapılmıştır. Detayları tezde verilen karşılaştırmalı simülasyon sonuçları, diyabet tanısında T2FNN mimarimizi kullanmanın etkinliğini kanıtlamıştır.

Anahtar Kelimeler: Diyabet, bulanık mantık, yapay sinir ağı, tanı sistemi, T2FNN

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List of Abbreviations

AI:	Artificial Intelligence
ANN:	Artificial Neural Network
CNN:	Convolutional Neural Network
BG:	Blood Glucose
CGM:	Continuous Glucose Monitoring
BMI:	Body Mass Index
DT:	Decision Tree
DL:	Deep Learning
ROC:	Receiver Operating Characteristic
FL:	Fuzzy Logic
GA:	Genetic Algorithm
GD:	Gestational Diabetes
KNN:	K-Nearest Neighbours
NB:	Naïve Bayes
NLP:	Natural Language Processing
RF:	Random Forest
SVM:	Support Vector Machine
GH:	Glycosylated Hemoglobin
PCA:	Principal Component Analysis
LR:	Logistic Regression
LDA:	Linear Discriminant Analysis
QDA:	Quadratic Discriminant Analysis
LSTM:	Long Short-Term Memory
SGD:	Stochastic Gradient Descent
SMO:	Sequential Minimal Optimization
SMOTE:	Synthetic Minority Over-Sampling Technique
RBF:	Radial Basis Function
MLP:	Multilayer Perceptron

CHAPTER I

Introduction

According to the international diabetes federation, the number of diabetes patients in the world will approach 600 million within approximately 15 years. It is important to know in early times about the diabetes because the cost of complications of diabetes is very high and the consequences are very fatal (Kadhm et al., 2018). Because of the late diagnosis of diabetes there are so many people who lose their organs and also they are lot of people who might suffer from loss of vision again in their life (Contreras & Vehi, 2018). In addition, heart and vascular disorders are frequently observed in diabetic patients. According to the World Health Organization, early diagnosis of diabetes is as important as early diagnosis of cancer (Franco et al., 2015).

Diabetes mellitus is the second most common disease after cancer and is caused by elevated blood sugar. If diabetes can be controlled at an early stage, the probability of getting rid of its fatal side effects increases. Early diagnosis of diabetes is vital. If diabetes mellitus, which is widespread throughout the world, is not controlled, it can cause paralysis, blindness, organ loss, heart diseases and neurological diseases. This is why the diagnosis of diabetes is important and vital.

With the early diagnosis of diabetes, the cost of the health systems and treatment will be reduced (Choubey & Paul, 2016). Country ‘s which are poor and underdeveloped do not have a budged for research and development this is why people in this countries can ‘t be treated and there for many peoples are harmed (Abhari et al., 2019).

Diabetes is a very important health problem that can be seen in every corner of the world. Diabetes is a disease that ranks 5th in disease-related deaths worldwide (Anjali & Pawar, 2017). The most important method in reducing diabetes-related deaths is to manage the glucose level in the blood. Around 9% of adults worldwide were diabetic in 2018. The vast majority of these patients have TYPE 2 diabetes (Bano & Khan, 2016). Diabetes is one of the biggest concerns of many societies, non-governmental organizations and health organizations (Lewis et al., 2016). Diabetes is a chronic disease which is a seen increase in blood sugar levels. The most important of the hormones involved in the regulation of blood sugar in the

body is the insulin hormone secreted by the beta cells of the pancreas (Rang & Dale, 2007).

If the pancreas cannot produce enough insulin hormone or if the produced hormone cannot be used effectively then the glucose which must turn into energy will be accumulate in the blood and causes blood sugar to rise (Amed & Oram, 2016). As a result of the absence or ineffectiveness of insulin, sugar that cannot enter the cell starts to rise in the blood (Dubey & Shrivastava, 2019). Diabetes occurs depending on hereditary or environmental factors. People who are genetically predisposed to diabetes are much more likely to develop diabetes. Diabetes can occur as a result of unhealthy living, not exercising, and eating unhealthy foods (Ahmed et al., 2013). In addition, being overweight and consuming sugar increases the risk of developing diabetes. Diabetes disease is seen in 3 types which are Type 1 diabetes also Type 2 diabetes and at least gestational diabetes (Rathour & Jain, 2018). 92% of diabetes patients are type 2 diabetes patients.

Type 1 diabetes disease usually begins before the age of 30 and can appear suddenly in overweight people (Fatemeh & Shahrokh, 2017). As a result of the immune system attacking the beta cells in the pancreas, it destroys the beta cells in the pancreas and therefore not enough insulin is produced and this is called Type 1 diabetes (Punthakee et al., 2018). Type 1 diabetes is a serious condition that cannot be cured by losing weight or paying attention to what they eat. Patients with type 1 diabetes have to inject insulin several times a day to prevent lethal levels of blood sugar and to avoid long-term complications. The initial symptoms of type 1 diabetes usually appear suddenly. When insulin production decreases, glucose accumulates in the circulatory system instead of being transported to body cells that need it for energy (Iyer et al., 2015). Type 1 diabetes manifests itself with symptoms such as excessive thirst and urination, weight loss, nausea, vomiting, feeling of hunger, dry and red skin, rapid breathing, abdominal pain and confusion.

Type 2 diabetes usually develops over the years, and its symptoms may not be noticed at first. In people with type 2 diabetes, insulin production is low or they cannot use it adequately (Ali et al, 2015). Usually there are no insulin injection requirements (Hunter, 2005). They can only be treated with diet or oral tablets (Patil & Tamane, 2016). Type 2 diabetes is more common in obese and people older than 45. However, it is also becoming rife in children and young adults as a result of increased obesity. Type 2 diabetes is the most type of diabetes which you can see. If

people with type 2 diabetes are not diagnosed early and treated, serious complications that can lead to death may develop (Jaafar & Ali, 2005). Millions of people all over the world live with Type 2 diabetes without even knowing about their disease or without accessing adequate medical care. Frequent urination, increased fluid consumption, feeling of hunger, weight loss, blurred vision, weakness and infections are temporary symptoms. When the blood glucose level is controlled, symptoms may disappear (Kumar & Agrawal, 2015). In some cases, complications such as peripheral neuropathy or coronary heart disease can be the first signs of diabetes (Contreras & Vehi, 2018). These complications can be controlled but not eliminated. Another possible initial sign of diabetes is hyperosmolar hyperglycaemia syndrome. Stroke, heart attack and infectious diseases can be seen as a result of the increase in the amount of glucose in the blood. Even though the amount of insulin does not require excessive ketone production, it is not high enough to prevent hyperosmolarity, where high blood glucose and high concentrations of sodium, glucose and other molecules that draw water from cells into the circulation system are present. Symptoms of hyperosmolar hyperglycaemia syndrome are dry mouth, feeling of hunger, vomiting, dry skin and skin burning.

Gestational diabetes is a type of diabetes associated with pregnancy. It occurs during pregnancy and usually disappears after pregnancy. Pregnant women who have had gestational diabetes are at risk of developing Type 2 diabetes later on. Pancreatic cells, which can secrete enough insulin before pregnancy, cannot secrete enough insulin during the pregnancy progresses, so blood sugar may rise during pregnancy even though there is no sign of diabetes before. Generally, pregnant women over 30 years of age with overweight are at a risk group for gestational diabetes if they have lots of cases of diabetics in their family the chance for getting gestational diabetes will be much more. Gestational diabetes usually resolves after birth, but the risk of recurrence is high in subsequent pregnancies.

Commonly used methods for diagnosing diabetes are the HbA1C test, fasting blood glucose and oral glucose tolerance test (Zhu et al., 2015). If detected early, the disease can be controlled, but methods are ineffective in early detection of the disease due to the high increase in the occurrence of the disease (Mansourpoor & Asadi, 2017). In diagnosing diabetes, skin thickness, family history, age, genetic predisposition and number of pregnancies are important.

The complete elimination of diabetes has not reached an acceptable level of success today (Deepika & Poonkuzhali, 2015). Early detection of diabetes prevents serious damage. Many patients with such diseases undergo lengthy tests and troublesome processes until they are properly diagnosed (Ambilwade et al., 2014). This causes a valuable waste of time to prevent progressive damage and for early treatment. Artificial intelligence in medicine is the biggest assistant of doctors in every field (Shields et al., 2015). Artificial intelligence has revolutionized health, as in every aspect of our lives. In the future, everyone in the healthcare industry, from specialist physicians to paramedics, is expected to use artificial intelligence technology (Vieira et al., 2004). Today, artificial intelligence and robotic technologies used in healthcare fields make healthcare services easier, faster and more successful (Sivanesan & Dhivya, 2017). Correct detection of diseases requires years of medical training. Even after this training, diagnosing is a difficult and time consuming task. In many fields of medicine, the demand for specialists has exceeded the supply, which stresses physicians and the diagnosis of diseases is even more delayed. Recently, great inventions have emerged in the automatic identification of diseases with artificial intelligence. With artificial intelligence, the diagnosis of diseases is much more economical and faster. It is a great advantage that artificial intelligence supported diagnostic systems are easy to use and accessible. Artificial intelligence has proven extremely useful in diagnosing a large number of different diseases today. Diabetes is one of these diseases (Eljil, 2014).

Purpose of the Study

The aim of this study was to develop an intelligent system that could offer high accuracy for diagnosis of Type-2 diabetes. Late and wrong diagnosis of diabetes can lead to fatal results. The main purpose of our study is to develop an easy-to-use algorithm and to use it effectively in the classification of diabetes. The usability and high accuracy of the developed algorithm are important for people. If diabetes is misdiagnosed, hyperglycaemic coma (comas due to high sugar), diabetic ketoacidosis (increased acidity in the blood), heart diseases, speech difficulties, blurred vision, memory loss, heart diseases, retinopathy, kidney diseases and nervous system disorders may occur. With the early and correct diagnosis of diabetes, all these deadly problems can be prevented.

State of the Problem

Diabetes is one of the most common diseases today. Diabetes causes many life-threatening diseases. The diagnoses of diabetes are based on input symptoms. The design of the highly accurate diagnostic system acquires importance. In the thesis type-2 fuzzy neural network system is proposed for diagnosis of diabetes. To implement the stated problem, the following stages have been done in this thesis.

- The review of the systems that are designed for diagnosis of diabetes
- The design of the structure for T2FNN system diagnosing the diabetes
- The development of learning algorithm of T2FNN system for diagnosis of diabetes
- The simulation of proposed T2FNN diagnostic system using statistical data
- The providing a comparative results in order to prove efficiency of designed system

Significance of the Study

The significance of this article is to present Type-2 Fuzzy Logic inference and the T2FNN method that comes out of its combination with Artificial Neural Networks. Presenting statistical values for 2 different data sets applied T2FNN method and providing a better understanding of Type-2 Fuzzy Logic. Is to explain the Type-2 membership function. Another significance is to shed light on the studies to be done using Type-2 Fuzzy Logic.

CHAPTER II

Review on Intelligent System for Diagnosing Diabetes

Literature Review

With the increase in the need for specialist doctors in the health sector, interest in artificial intelligence-supported health solutions has increased. Today, artificial intelligence assisted diagnosis systems, rehabilitation systems and health management systems are frequently used. Computer-aided artificial intelligence systems are increasing day by day in order to carry out health services more easily. Autonomous systems are preferred to reduce costs and increase success. The biggest advantage of artificial intelligence assisted diagnosis systems is that they respond in a timely manner and with high accuracy. There are also diabetes diagnosis systems among artificial intelligence supported systems. In the literature, different studies have been carried out to classify diabetes with artificial intelligence.

Beloufa and Chikh (2013), developed a system for diabetes detection with hybrid architecture artificial bee colony optimization. They achieved 84.21% accuracy with 10-fold cross validation. The authors applied hybrid architecture artificial bee colony optimization to the PIMA dataset of 768 patients. The performance of the model was increased by adding the mutation operator (Beloufa & Chikh, 2013).

Polat et al, (2008), the authors reported 79.16% accuracy with the support vector machine method using the Pima data set consisting of 768 patients (Polat et al, 2008).

Polat and Gunes (2007), presented an architecture combining genetic algorithms and artificial immune system. With the architecture consisting of these two structures, they achieved 75.87% accuracy in cross validation (Polat & Gunes, 2007).

Tand and Tseng (2009), obtained 81.6% accuracy in estimation of genetic algorithm based weight method (Tand & Tseng, 2009).

Temurtas et al, (2009), presented a probabilistic neural network method with the Pima dataset consisting of 768 patients. They obtained 79.62% accuracy with the proposed probabilistic neural network method, and they obtained 78.05% accuracy on the same data set with the multilayer neural network method (Temurtas et al, 2009).

El-Sappagh et al., (2015), created an ontology-based fuzzy logic architecture. In the present study, the authors examined 60 diabetic patients and achieved an accuracy of 97.67% with only the cases with Type 2 diabetes. In the study they presented, age, gender, body mass index, HBA1C and 2-hour fasting blood glucose status of the cases were examined (El-Sappagh et al, 2015).

Polat and Güneş (2007), applied the (PCA)Principal component analysis method and the ANFIS method to the Pima dataset in their studies. The authors achieved a maximum accuracy of 89.47% in the study they presented (Polat & Güneş, 2007).

Seera and Lim (2014), presented a hybrid study based on fuzzy min-max and random forest. In their studies using the Pima dataset, 78.39% accuracy was obtained with the hybrid system (Seera & Lim, 2014).

Aslam et al, (2013), classified the Pima dataset consisting of 768 samples. In their study, a 3-stage technique with genetic programming was used. In the study, 87% accuracy was obtained without cross validation and 80.5% accuracy with 10-fold cross validation (Aslam et al, 2013).

Ahuja et al, (2019), applied 5 classification algorithms to the PIMA dataset consisting of 768 patients. These classification algorithms are Support Vector Machine (SVM), Multilayer Perceptron (MLP), Logistic Regression, Random Forest and Decision Tree. When comparing 5 different classification algorithms in the study, the MLP classifier algorithm showed the highest accuracy with 78.7%. In the same study, 65.97% accuracy was obtained with 4-fold cross validation (Ahuja et all, 2019).

Nabi et al, (2017), used 4 different algorithms simultaneously to classify diabetes. In the presented study, they provided 80% accuracy by applying four classification algorithms, namely J48, Naif Bayes, Logistic Regression and Random Forest (Nabi et all, 2017).

Maniruzzaman et al, (2017), applied LDA, Quadratic Discriminant Analysis (QDA), Gaussian Process Classifier (GPC) and Naïve Bayes classification algorithms for diabetes classification. In their study, the highest accuracy was obtained with the Gaussian Process Classifier algorithm. They achieved 82% accuracy with the Gaussian Process Classifier algorithm (Maniruzzaman et all, 2017).

Sisodia and Sisodia (2018), applied 3 different classification methods to the PIMA dataset consisting of 768 patients. In the study, Support Vector Machines, Na-

ïve Bayes and Decision Tree algorithms were applied. The highest accuracy was obtained with 76.3% Naïve Bayes algorithm (Sisodia & Sisodia, 2018).

Kandhasamy and Balamurali (2015), used KNN, J48, SVM and Random Forest algorithms to classify diabetes using the pima dataset. In the study, the highest accuracy was obtained with the J48 algorithm. In the study, 73.82% accuracy was obtained with the J48 algorithm (Kandhasamy & Balamurali, 2015).

Swapna et al, (2018), used CNN and CNN-LSTM methods. In the study, they proposed a model that facilitates the diagnosis of diabetes by using heart rate signals. With an algorithm consisting of a combination of CNN-LSTM, 95.1% accuracy was obtained (Swapna et al, 2018).

Mercaldo et al, (2017), applied a deep learning algorithm to the PIMA dataset consisting of 768 patients. The authors obtained 77% accuracy with the deep learning method in the present study (Mercaldo et al, 2017).

Rabina and Chopra (2016), presented a diabetes prediction model using a supervised and unsupervised learning method with the WEKA application. Bayesian Network, Naïve Bayes, Logistic Regression, Multi-Layer Detection (MLP), SGD and SMO algorithms were used in this study. The highest value was obtained with a multilayer perceptron with an accuracy of 77.7%. (Rabina & Chopra, 2016).

Sreedevi and padmavathamma (2015), compared the genetic algorithm and the Minkowski Distance method with multiple functions. In the study, the highest success was obtained with the Minkowski function with an accuracy of 72,214%. In the study, the authors used the PIMA dataset (Sreedevi & padmavathamma, 2015).

Sayadi et al, (2017), developed a decision tree model for the detection of type 2 diabetes. In this developed decision tree, patients ‘ age, gender, body mass index, blood pressure values are presented as input to the system. With the decision tree model realized with Weka software, 88% accuracy was obtained (Sayadi et al, 2017).

Farahmandian et al, (2015), applied SVM, KNN, Naïve Bayes, ID3, C4.5, C5.0, and CART algorithms for the diabetes dataset. In the study, the highest accuracy was obtained with the SVM algorithm. In the study presented by the authors, an accuracy of 81.77 was obtained with the SVM algorithm (Farahmandian et al, 2015).

Mirza et al, (2018), used the SMOTE algorithm and then proposed a system for diagnosing diabetes by creating a decision tree with the data obtained. In the 2-stage study presented by the authors, an accuracy of 94.7% was obtained. The PIMA dataset was used in the study (Mirza et al, 2018).

Sa ‘di et al, (2015), used the PIMA dataset consisting of 768 patients. Naive Bayes, RBF Network and J48 data mining methods were used on the PIMA dataset consisting of type 2 diabetes patients. These algorithms have been tested with Weka software. The highest accuracy in the study was obtained with the Naive Bayes algorithm. In the study, 76.95% accuracy was obtained with the Naïve Bayes algorithm (Sa ‘di et al, 2015).

Choubey and Paul (2016), applied a two-step method to the PIMA dataset for the detection of diabetes. In the first stage, the Geneti Algorithm method was applied to the dataset. In the second stage, Multilayer Perceptual Neural Network (MLP NN) was used to classify the selected features. In the presented study, 79.13% accuracy and 0.842 ROC were obtained (Choubey & Paul, 2016).

Iyer et al, (2015), developed a diabetes diagnosis system with Decision Tree and Naïve Bayes algorithms. The developed algorithm was created with WEKA. 76.95% accuracy was achieved in the system created with the WEKA interface (Iyer et al, 2015).

Woldemichael and Menaria (2018), used back propagation algorithm, J48 algorithm, Naïve Bayes algorithm and Support Vector Machines to detect diabetes. They obtained results with 5-fold cross validation for the PIMA dataset consisting of 768 patients. According to the results obtained, 83% accuracy was obtained with the Backpropagation Artificial Neural Network. Study results showed that other algorithms presented in the same study offer less accuracy (Woldemichael & Menaria, 2018).

Mala (2019), presented an algorithm for the early detection of diabetes using the PIMA dataset of 768 patients. They achieved 78% accuracy with the Support Vector Machines architecture algorithm (Mala, 2019).

Krishnaveni and Sudha (2012), tested the diabetes dataset with KNN, Naive Bayes and Support vector machine algorithms. The author achieved 74% accuracy in this study (Krishnaveni & Sudha 2012).

Rajesh and Sangeetha (2012), used the C4.5 algorithm for classify diabetes. The authors obtained 91% accuracy with Feature inference analysis in the present study (Rajesh & Sangeetha 2012).

Islam et al, (2019), presented a diabetes diagnosis system with the data set they created. The created data set was tested with 3 different algorithms. These algorithms are Bagging algorithm, Logistic Regression algorithm and Random Forest algorithm,

respectively. The highest accuracy in the study was obtained with the Random Forest algorithm. They achieved 90% accuracy with the Random Forest algorithm. They provided 89% accuracy with the Bagging algorithm and 83% accuracy with the Logistic Regression algorithm (Islam et al, 2019).

Jasim et al, (2017), developed diabetes classification systems with K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) algorithms. They tested the datasets consisting of 768 patients with the algorithm they modified. In this study presented by the authors, they achieved 80% accuracy in Artificial Neural Networks and 77% accuracy with the K-Nearest Neighbor Algorithm (Jasim et al, 2017).

Wei et al, (2018), developed an architecture to classify diabetes with Deep Neural Network (DNN) and Support Vector Machine (SVM). They worked with many features such as age, pregnancy, glucose, blood pressure, and BMI in the data set used. With the architecture presented in the study, 77% accuracy was obtained (Wei et al, 2018).

Anderson et al, (2016), presented a study to monitor and predict diabetes with the inputs of BMI, age, sex, smoking status and hypertension. The authors obtained 75% Accuracy, 80% Sensitivity and 73% Specificity in the study they presented (Anderson et al, 2016).

Suryakirani and Porkodi (2018), obtained results with classification algorithms using the diabetes dataset. In the presented study, they obtained 73% accuracy with J48 algorithm, 70% accuracy with Random Forest, and 67% accuracy with Naïve Bayes algorithm (Suryakirani and Porkodi, 2018).

Shuja et al, (2018), proposed a system to predict diabetes using data mining technique. In this proposed system, PIMA data set collected by data mining method was used. For the inconsistencies found in the data set, firstly, the data set was arranged, then the results were obtained with the SMOTE algorithm. The inputs in the dataset used are age, waist circumference, BMI, systolic blood pressure, diastolic blood pressure, gender, and family history of illness, respectively. In the presented study, they achieved 85% accuracy (Shuja et al, 2018).

Alkaragole and Kurnaz (2019), presented a hybrid model to classify diabetes. In this hybrid system presented, results were obtained with Support Vector Machines and Random Forest algorithms. The hybrid model presented in the study provided 94% accuracy (Alkaragole & Kurnaz, 2019).

Geman et al, (2017), presented Artificial Neurol Fuzzy Inference architecture to classify Diabetes. The architecture coded through the Matlab toolbox has been trained and tested with the PIMA dataset. In the presented study, the authors achieved 85% accuracy with the training set and 84% accuracy with the test set (Geman et al, 2017).

Vijayan and Anjali (2015), compared AdaBoost algorithm, Support Vector Machine, Naive Bayes and Decision Tree algorithms for diabetes prediction. Among the 4 algorithms compared in the presented study, the highest accuracy was obtained with the AdaBoost algorithm. The authors achieved 80% accuracy with the AdaBoost algorithm in this diabetes prediction study they presented (Vijayan & Anjali, 2015).

Farooqual and Ritika (2018), used KNN, Support Vector Machines, Decision Trees and Random Forest algorithms to classify diabetes. In the present study, results were obtained with the Pima dataset. In the presented study, the authors obtained the highest accuracy with the Random Forest algorithm. They obtained 96% accuracy with Random Forest algorithm from the PIMA dataset tested with 4 different machine learning algorithms (Farooqual & Ritika, 2018).

The literature review have shown that many different methods have been developed for diagnosis of diabetes. To give an example, diabetes diagnosis with artificial neural networks (Temurtaş et al., 2008), diabetes diagnosis with hybrid system (Kahramanlı and Allahverdi, 2008), SVM-based diabetes diagnosis systems (Guira et al., 2017), (Polat et al. ., 2008), decision tree and random forest algorithms supported diabetes diagnosis systems (Singh et al., 2017), (Zou et al., 2018), many sets of machine learning models have been developed. For the diagnosis of diabetes, statistical data and different algorithms related to learning networks are presented (Erkaymaz et al., 2017). The authors developed a diabetes diagnosis system with a neural network-based method titled “small world feed forward” (Erkaymaz et al., 2017).

Christopher et al., (2018) used the swarm optimization method for the design rule basis for diabetes diagnosis and presented the results (Christopher et al., 2018). Kannadasan et al., (2018) presented a deep neural network algorithm based on stacked autoencoders for the extraction of diabetic features and classification of diabetes using the diabetes dataset (Kannadasan et al., (2018).

Statistical methods were used to classify the data sets of the presented models. Disease diagnosis processes are one of the most challenging processes. At the stage of

disease diagnosis, artificial systems use inputs and outputs from statistical data. The connection established between inputs and outputs affects success. In the datasets, the person ‘s health status is characterized by the person ‘s inputs. In some cases, it is very difficult to diagnose the disease. It can be difficult to relate input and output values in complex data sets.

Artificial systems have to decide by dividing the input signals into different ranges. The ranges of the input signals are uncertain. Also, there may be noisy samples inside the input signals. Due to its complexity, errors may occur during the diagnosis of the disease. For example, illnesses may react differently to each person. Incomplete patient data and the complexity of the disease can lead to misdiagnosis.

Fuzzy logic is often used for such complex problems. One of the most suitable approaches for problem solving in complex data sets is fuzzy logic. The fuzzy logic method can be used to find the optimal relationship between the input and output variables. Fuzzy logic-based systems are more suitable for dealing with uncertainty in medical diagnoses. Fuzzy logic works with linguistic terms with numerical approximation to represent more precise information (Zadeh, 1965), (Zadeh, 1975).

Bressan et al., (2020) applied a fuzzy rule-based method for the diagnosis of type-2 diabetes in the literature (Bressan et al., 2020). Ghazavi and Liao (2008) presented fuzzy classification algorithm and ANFIS model for feature extraction using medical data (Ghazavi and Liao 2008). Feng et al., (2015) presented a hierarchical fuzzy-based classification algorithm with variable codes using evolutionary DNA coding (Feng et al., 2015). Beloufa and Chikh (2013) presented a modified bee colony algorithm and fuzzy classifier to classify diabetes (Beloufa & Chikh 2013).

Ramezani et al., (2018) presented a hybrid system based on logistic regression and ANFIS for diabetes diagnosis (Ramezani et al., 2018). Mansourypoor and Asadi (2017) used a hybrid of fuzzy rule base and reinforcement learning for the diagnosis of diabetes (Mansourypoor & Asadi 2017). El-Sappagh et al., (2015) presented a semantic fuzzy oncology-based reasoning algorithm for diabetes diagnosis (El-Sappagh et al., (2015). Siva and Manikandan (2019) classified diabetes mellitus into classes using fuzzy rules optimized with the gray wolf algorithm (Siva and Manikandan (2019).

Type-1 fuzzy logic may not always give good results in complex problems. Because Type-1 fuzzy sets are two-dimensional, they cannot cope with extreme uncertainties (Mendel, 2017), (Karnik and Mendel, 1999). To cope with such uncertainties,

Type-2 fuzzy sets should be used. Type-2 fuzzy sets were presented by Lütfi Zadeh as an alternative to Type-1 fuzzy sets. Type-2 fuzzy sets can cope with such uncertainties since they have a 3-dimensional membership function. Type-2 fuzzy sets were developed by Mendel and his students (Mendel, 2017), (Karnik and Mendel, 1999).

Type-2 fuzzy systems are used in the literature to solve engineering problems (Abiyev, 2010), (Liang & Mendel, 2000), (Abiyev et al., 2011), (Hagras, 2004), (Liu et al., 2007), (Castillo & Melin, 2008),(Biglarbegian, 2010), (Abiyev & Kaynak, 2010), (Lin et al., 2015),(Abiyev & Abizada, 2021), (Abiyev, 2014).

Type-2 fuzzy systems have been used for the diagnosis of many different diseases (Shafaei et al., 2018), (Mohammed & Hagras, 2018), (Lee et al., 2010), (Goharimanesh et al., 2015). Shafaei et al., (2018) presented a Type-2 fuzzy set-based regression model to detect retinopathy, a diabetic disease (Shafaei et al., 2018). Mohammed & Hagras, (2018) presented a type-2 fuzzy set diabetic diet recommendation algorithm. In the presented system, it is aimed to control the disease and bring the patients to a healthy life (Mohammed & Hagras, (2018). Lee et al., (2010) presented a type-2 fuzzy set ontology model for diabetic diet recommendations (Lee et al., 2010). Goharimanesh et al., (2015) presented an architecture with a type-2 fuzzy set to control blood sugar in patients (Goharimanesh et al., 2015).

As seen in the literature review, studies have been carried out for the diagnosis of diabetes. The main issue was the highly accurate design of the diagnostic system.

As shown the diabetes is the most dangerous and common disease after cancer. In people with diabetes, the wounds heal late, they have difficulty in seeing, vascular diseases occur, they have the risk of paralysis, diseases may develop in the internal organs. All these side effects can be controlled by detecting diabetes at an early stage. Uncontrolled diabetes can cause death. Many different studies have been conducted for the diagnosis of diabetes and many different models have been presented. Diabetes classification methods were carried out with statistical approaches to diabetes datasets. Studies in the literature could not provide high accuracy due to the complex structure of diabetes datasets. Another reason for not obtaining high accuracy is the noise in the data sets and incomplete patient records. Fuzzy Logic approach is one of the best methods for noisy data in complex datasets such as diabetes datasets and datasets with missing records. It is more convenient to design Fuzzy Logic to identify uncertainties and find relationships between variables. Fuzzy Logic approach is divided into Type-1 fuzzy sets and Type-2 fuzzy sets. Type-2 fuzzy sets were proposed by Lütfi Zadeh as

a more advanced version of Type-1 fuzzy sets. Type-1 fuzzy sets have not been effective enough in databases with uncertainties. Such uncertainties should be handled with Type-2 fuzzy sets.

CHAPTER III

Type-2 Fuzzy Neural System for Diagnosing Diabetes

Type-2 Fuzzy Logic

Lotfi Zadeh invented fuzzy set theory while studying at the University of Berkeley Electrical and Electronics Engineering Research Laboratory. He published his work on the solution of a technical problem under the title of Fuzzy Sets in the Journal of Information and Control in 1965. This was a starting point. This new step brought progress in the depths of engineering in the shortest possible time. Success was achieved in the applied high-quality work. Zadeh laid the groundwork for creating rule processing and transferring it to the machine. He developed an inference model with a machine, using all kinds of knowledge and experiences in human life. In its simple form, it can be defined as a decision-making mechanism design. However, it should be taken as an example that it looks more like a human than a machine.

Fuzzy logic is based on fuzzy sets and subsets. In the classical approach, an object is either a member of the set or it is not. When expressed mathematically, it takes the value “1” if the object is a member of the set in terms of its membership relationship with the set, and “0” if it is not a member of the set. Fuzzy logic is an extension of classical set theory. In a fuzzy set, each object has a degree of membership. The degree of membership of the object can be any value in the range (0, 1) and is represented by the membership function $\mu(x)$.

If we accept the normal room temperature as 23 degrees, according to the classical set theory, we accept the temperatures above 23 degrees as hot and the membership degrees in the hot set of these degrees will be “1”. Temperature degrees below 23 are cold and membership degrees in the hot cluster become “0”. These values are reversed when we base the cold set. In the fuzzy set approach, membership values take values in the range of [0,1]. For example, the membership degree may be “0” for a temperature of 14 degrees, and the membership value may be “0.25” for a temperature of 23 degrees.

Unlike classical sets, in fuzzy sets, the membership degrees of the elements (objects) can change infinitely in the range of [0, 1]. They are a complete set of degrees of membership, continuous and uninterrupted. Binary variables such as cold-warm, fast-slow, light-dark in exact sets are used. In fuzzy sets, on the other hand,

they are expanded with flexible qualifiers such as a little cold, a little warm, and a little dark, and simulate real-world problems. The difference from definite clusters is that the membership of the cluster at the source of the information does not have strictly defined preconditions and the variables are in a certain range. Fuzzy logic is the principle of creating an artificial intelligence application. The key to fuzzy logic is to arrive at a conclusion.

Fuzzy logic system works similar to the reasoning process of humans. Fuzzy logic consists of fuzzy variables and fuzzy sets. The main task of fuzzy logic is to try to decide mathematically which of these variables and sets belong to each other. The flexibility of fuzzy logic comes from the fuzzy boundaries of these sets. Let ‘s just give an example. A conventional oven operates on a full temperature basis. When the oven reaches any selected temperature, a thermometer in the oven cuts off the power to the oven heater, and activates it again when the temperature drops below a certain other. This logic applies the same no matter what happens inside the oven. In a microwave oven with fuzzy logic temperature control, the result is not dependent on exact temperatures. Instead the process looks like this: “IF (process is too cold) AND (process is cooling) THEN (add more heat)” or “IF (process is too hot) AND (process is cooling) THEN (heating now). “as.

Fuzzy logic consists of software trying to make decisions like humans. The fuzzy logic approach is generally preferred for complex problems. The advantages of fuzzy logic algorithms are that they are easy to code and user-friendly. The fuzzy logic algorithm is similar to the natural language algorithms. They save on storage as they require less code and fewer instructions. In addition to these advantages, disadvantages can be seen from time to time due to the lack of precision of fuzzy logic. Every step of fuzzy logic should be tested and controlled. Expert knowledge is always needed to create fuzzy logic.

Fuzzy logic has many advantages over other algorithms.

- The human thought system is focused on processing verbal, not numerical, information. In other words, the human mind ‘operates with words ‘. It uses linguistic values for what it is trying to express. Because fuzzy logic works similarly, it can produce results that approximate human logic.
- Accessing the numerical data necessary to solve real-world problems is often cumbersome and costly. In these cases, where we do not have

enough information, fuzzy logic; It can produce reasonable results even in uncertain situations by using human ‘s value judgments, thinking and decision-making power.

- Experts who design the fuzzy system may have non-numerical or mathematically modelable experience of the system. For example: A teacher who knows his students well enough can predict the grades that students can get according to the difficulty level of the exam. For each student, very approximate estimates can be made, but it is very difficult to formulate these estimates. In such cases where numerical information cannot be reached; Transfer of experiences to a machine or computer is possible with fuzzy logic. Because it can work close to the human mind, it is understandable for many control methods.
- It ‘s not hard to create the theories and math that works in the background.
- Thanks to its flexible structure, in uncertain probability situations; It can even work well with complex and non-linear functions and continuous values(i.e. only values that we know to be in a certain range).
- A fuzzy system can be modelled with the spoken language of daily life. In this respect, while developing fuzzy systems, it allows to work effectively even with people who do not have technical knowledge in programming and system design.
- Since fuzzy logic includes classical logic, every system created with classical logic can also be created with fuzzy logic.

Fuzzy logic is an outstanding field of study that has gone beyond the scope of classical logic and tries to build the logic model that people actually own and use on computers and machines.

The kernell of fuzzy system is fuzzy rul base that includs fuzzy values in the antecedant and consequent parts of the rules. It has been shown that fuzzy values can be employed to induce models from trendy and subjective concepts for evaluation purposes. There may be different expert opinions in the expression of linguistic values of the variables. For example, different experts may specify the numeric transformation of the linguistic value “Normal” differently. (Membership functions of linguistic value “Normal” can be formulated differently with the different experts). In such ca-

ses, type-1 fuzzy sets cannot handle the uncertainties. Type-2 fuzzy sets that extencion of type-1 fuzzy sets can be an excellent framework for handling these uncertainties. Because of membership functions of the general type-2 fuzzy set is three-dimensional it can directly model uncertainties. The increase of dimension complicates computations using type-2 fuzzy sets. To simplify the calculation, interval type-2 fuzzy membership function is applied to describe these uncertainties.

Mamdani and TSK (Takagi-Sugeno-Kang) fuzzy systems are generally preferred for type-2 fuzzy sets design. Mamdani inference is the most widely used fuzzy inference method. The reason why Mamdani inference is preferred is that it appeals more to human perception. In addition, the Mamdani inference stands out with its easy design and easy interpretation. In Mamdani inference, the input and output values are fuzzy values. In this system, membership values are calculated according to the rules triggered by the fuzzy values in the input. The values resulting from these calculations are given to the Max or Min operator according to their logical connectors. The logical connectors found in the system are two as “and” and “or”. The most important information we need to know here is that if the facts in the rule are connected with “and”, the calculated membership values are given to the “min” operator. If the facts passing through the rule are connected to each other with “or”, they are given to the “max” operator. The goal here is to return the smallest or largest of multiple values.

Sugeno inference is mostly preferred for control problems. The most important difference between sugeno inference and mamdani inference is that sugeno inference gives the output value as a function. In Mamdani inference, the output value is a fuzzy value. The biggest advantage of this difference is that it is much easier to calculate defuzzification operations in sugeno extraction. In Sugeno extraction, a single value is obtained after calculating the result of the rules. It finds this value by calculating the weighted average of the results. As a result of the rules, a single value is calculated instead of a membership function. In Sugeno inference, rule structures are created as “IF”, “AND” and “THEN”.

When we compare Mamdani and Sugeno inference methods, the mamdani method better reflects knowledge and rules. Sugeno extraction is easy to apply. Mamdani inference is similar to human decision making. The computation time of Sugeno inference is much less. Mamdani inference is very complex and time consuming. Sugeno subtraction is very suitable for dynamic control problems.

It has been stated that Sugeno type fuzzy systems have high accuracy in identification and classification problems (Abiyev & Kaynak 2010). In the thesis the type-2 sugeno system is used for diagnosing diabetes.

Design of Type-2 Fuzzy Neural System

The first question to be solved in the Type-2 fuzzy logic TSK approach is the creation of rules. The fuzzy logic approach consists of rules and membership functions. The first thing to do in Type-2 fuzzy logic TSK model is to create IF-THEN rules. In this thesis, Type-2 TSK fuzzy logic rules with multiple inputs and multiple outputs were created. The formula used is presented in equation 1.

$$\text{IF } x_1 \text{ is } \tilde{A}_{1j} \text{ and } \ldots \text{ and } x_m \text{ is } \tilde{A}_{mj} \text{ THEN } y_1 = \sum_{i=1}^{m} w_{i1} x_i \text{ and} \ldots \text{and } y_r = \sum_{i=1}^{m} w_{ir} x_i \quad (1)$$

Here $x_1, x_2, \ldots, x_m$ represents input variables, $\tilde{A}_{ij}$ is type-2 interval fuzzy sets associated with the *i*-th input signal and *j*-th rule and represented by triangle forms. y_j $(j=1,..,r)$ are linear functions, w_{ij} are coefficients of linear functions, $i=1,..,m$, $j=1,..,r$, $k=1,\ldots,n$, where m is number of input signals, r is number of rules, n is number of output signals.

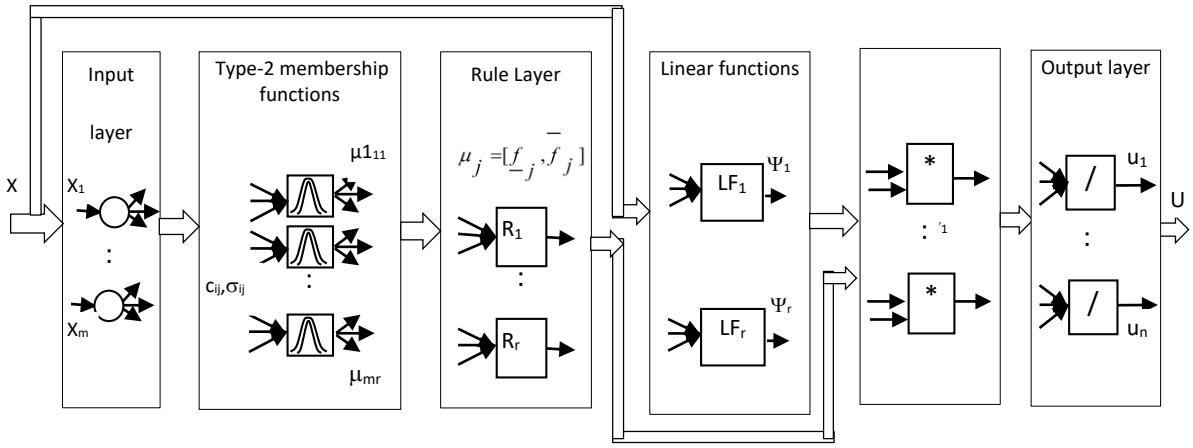
The first problem in the design of fuzzy logic systems is to create the antecedent and conclusion stages of the rules to be created. Neural network architecture and learning algorithms were combined to create the Type-2 TSK fuzzy logic model we presented in this study. In this study, T2FNN (Type-2 Fuzzy Neural Network) structure, which is obtained by integrating Neural networks learning algorithm and Type-2 fuzzy logic inference, is used for the diagnosis of diabetes.

The development of the T2FNN system includes the determination of the structure and the proper values of the unknown coefficients of the antecedent and the consequent parts of each rule (Abiyev & Kaynak, 2010). Structure selection of T2FNN includes determination the number of fuzzy rules (layer 3) from the training data and the number of fuzzy sets (layer 2) for each input variables. These two parameters are closely dependant. That is, selection the value of first parameter depends on selection the value of later one. There are some approaches for structure selection. One is the use of clustering approaches and according to cluster numbers selecting number of fuzzy rules (or number of hidden neurons in layer 3) in type-2 FNS. The

clustering approaches could be used for classification of input space and determination number of rules. Another approach uses the rule firing strength as a criterion for generation of new rule. In the paper we apply clustering approach for structure selection from (Abiyev & Kaynak, 2010) and pay more attention for determination of unknown parameters of T2FNN. After selection of structure the learning of parameters of T2FNN system starts. Let us consider the design of T2FNN when the membership functions are of Gaussian type as in (1). If both (c and σ) parameters of the Gaussian function are considered to be uncertain (within certain intervals), the parameter space of the system can become very large. In this thesis, only one of these parameters is assumed to be uncertain. However, the learning rules are derived for both cases, i.e fixed STD and uncertain mean and uncertain STD and fixed mean. It is to be noted that the fixed values are also subject to parameter adjustment (Abiyev & Kaynak, 2010). Figure 1 shows the T2FNN architecture created in this thesis.

Figure 1.

Architecture of Type-2 Fuzzy Neural System

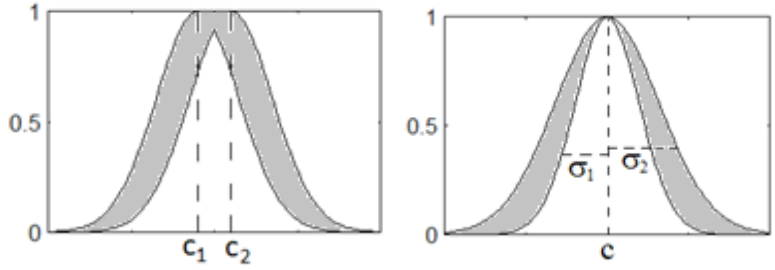


In the thesis the parameters of membership functions are represented by uncertain mean and fixed STD. In the first layer of T2FNN model Fig.1, the input layer is used to distribute the signal. The second layer contains the type-2 membership functions used to represent the unknown parameters of the antecedent part of the rules (1). The membership functions of the presented model are represented using Gaussian.

$$\mu 1_j(x_i) = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}} \qquad (2)$$

Where x_j are input signals, c_{ij} and σ_{ij} are the center and width of the membership functions. Uncertainties can be associated to the mean $c_{ij} \in [c_{ij}^1, c_{ij}^2]$ and width $\sigma_{ij} \in [\sigma_{ij}^1, \sigma_{ij}^2]$ of mebersip functions. Fig. 2(a) and 2(b) depicts the Gaussian membership functions with uncertain mean and uncertain width, respectively. We use interval type-2 membership functions, with an uncertain mean as shown in Fig.2(a). Each point of the membership function is characterized by the upper $\overline{\mu}(x)$ and lower $\underline{\mu}(x)$ membership values that are calculated using (2).

Figure 2.
Gaussian Type-2 fuzzy Set with an Uncertain Mean (a) and Uncertain Width (b).



(a) (b)

The third layer performs the product operation.

$$\mu_{\tilde{A}_k^i}(x_k) = [\underline{\mu}_{\tilde{A}_k^i}(x_k), \overline{\mu}_{\tilde{A}_k^i}(x_k)] = [\underline{\mu}^i, \overline{\mu}^i] \qquad (4)$$

Then, the firing power of each rule in the rule layer is calculated. The t-norm "min" inference is applied to calculate the firing power of each rule. The outputs of the rule layer are determined as follows.

$$\begin{aligned} \underline{f} &= \underline{\mu}_{\tilde{A}_1}(x_1) * \underline{\mu}_{\tilde{A}_2}(x_2) * \ldots * \underline{\mu}_{\tilde{A}_n}(x_n); \\ \overline{f} &= \overline{\mu}_{\tilde{A}_1}(x_1) * \overline{\mu}_{\tilde{A}_2}(x_2) * \ldots * \overline{\mu}_{\tilde{A}_n}(x_n) \end{aligned} \qquad (4)$$

Where * is t-norm min operator. In order to determine the fuzzy outputs of the rules, the firing powers of the Type-2 rules in Formula 4 must first be obtained. These

processes are implemented in the fourth and fifth layers. Type reduction and defuzzification processes are applied in the fifth and sixth layers. The inference engine presented in references (Biglarbegian, 2010) and (Abiyev & Kaynak, 2010) is used to determine the crisp output of the system.

$$u_k = \frac{p\sum_{j=1}^{r} \underline{f}_j y_j v_{jk}}{\sum_{j=1}^{r} \underline{f}_j} + \frac{q\sum_{j=1}^{r} \overline{f}_j y_j v_{jk}}{\sum_{j=1}^{r} \overline{f}_j} \qquad (5)$$

$$y_j = \sum_{i=1}^{m} x_i w_{ij},\ i=1,..,m,\ j=1,..,r,\ k=1,\ldots,n \qquad (6)$$

Here $\overline{f}_j$ and $\underline{f}_j$ are computed using (4). x_j are input signals, y_j are outputs of liner functions, w_{ij} and v_{jk} are coefficients of the linear functions. p and q parameters are used to adjust the lower and upper portions in the final output.

After finding the output signal of the system, the training of the parameters is started. Training allows updating the values of $c1_{ij}$, $c2_{ij}$ and σ_{ij} coefficients of membership functions and w_{ij} and v_{jk} coefficients of the linear functions and output layer correspondingly. In the paper, the gradient descent algorithm is applied for correcting the values of the unknown coefficients. The readers can refer to the references (Abiyev & Kaynak, 2010) for the detail of the learning algorithm.

CHAPTER IV

Simulation of T2FNN System for Diagnosing Diabetes

Analysis of Diabetes Data

Pima and extended Pima datasets are used for this study. Here, we consider the design of T2FNN diabetes identification systems using datasets. For the system ‘s design, we used the extended Pima dataset containing 2000 data samples and the old version Pima dataset containing 768 data samples. An expanded version of the datasets is available at https://www.kaggle.com/johndasilva/diabetes. T2FNN, in which we obtained the highest results for the design of the diabetes diagnosis system, were processed for both databases in this thesis.

The first version of the Pima diabetes dataset consists of 768 patients, and the second version consists of 2000 patients. There are 8 entries in total in this data set. The extended Pima dataset consists of 2000 patients. Since the research announced in the literature about the Pima dataset was carried out with the old version, results were obtained with 768 patient samples. Conducting this study with 2000 samples has affected the quality of the article. There are 8 inputs in this data set, which are numbers of pregnancies, oral glucose tolerance test, blood pressure, triceps skinfold thickness, hourly serum insulin value, body mass index, diabetes pedigree function and age. Table 1 provides explanations about the extended Pima dataset.

Table 1.

Explanations of Pima Datasets Attributes

Attribute	Attribute Description
Pregnant	Number of times pregnant
Plasma gluco-	Oral glucose tolerance test
Diastolic BP	Diastolic blood pressure
Triceps SFT	Triceps skinfold thickness
Serum insulin	Hour serum insulin (mu
BMI	Body mass index (kg/ (m) ^{2})
DPF	Diabetes pedigree function
Age	Age (years)
Class	Class variable (0 or 1)

In the data set created, there are 2 outputs diabetes or healthy in response to all these inputs. All entries used in the data set provide information about diabetes. All entries in the database are the most important factors that determine diabetes. The first input used in our data set is the number of pregnancies. The risk of getting diabetes is higher for women with more than 3 pregnancies. The second input in the data set is the 2-hour plasma glucose concentration. The higher the plasma glucose concentration above 140, the higher the risk of diabetes. The third input in the data set is the blood pressure value. A blood pressure value greater than 90 increases the risk of diabetes. Next is the fourth entry is skinfold thickness, this gives us information about diabetes. It has been observed that the thickness of the skinfold in diabetic patients is more significant than expected and this value should be 15 on average under normal conditions, whereas it is generally more than 23 in diabetic patients. Insulin resistance was used as the fifth entry in the Pima dataset. Insulin resistance is a disease that develops by converting the consumed sugary and carbohydrate-rich foods into a nutritional habit. In addition to causing fat in the liver, it also affects vital organs such as the heart and brain. It invites diseases such as heart attack and stroke. After a while, the pancreas gets tired of producing insulin and becomes lazy and the blood sugar level starts to rise. Accordingly, it first manifests itself as low blood sugar, and then as diabetes mellitus after being hungry quickly. An insulin resistance greater than 166 is an indicator of diabetes risk. An important step is the sixth input in this dataset it is the body mass index. A body mass index of more than 30 can cause diabetes. This penultimate entry is the diabetes pedigree function. Family pedigree does not give precise information about diabetes, but it represents a predisposition. family history of diabetes can increase the risk of diabetes. Diabetes pedigree function values above 0.5 may pose a risk of diabetes. The last and the eight inputs used in the extended Pima data set is the age of the patients. Type 2 diabetes usually occurs after a certain age. Studies have shown that Type 2 diabetes usually occurs after the age of 30.

Table 2 and Table 3 presents the fragment of statistical data taken from the Pima Diabetes datasets. These examples consist of input and output values in our datasets for 15 different patients or healthy individuals. Also, in the tables outcome section of “1” represents diabetes, and “0” represents no diabetes.

Figure 3.

Density Display of Outcome Values of Extended Pima Dataset (2000 samples).

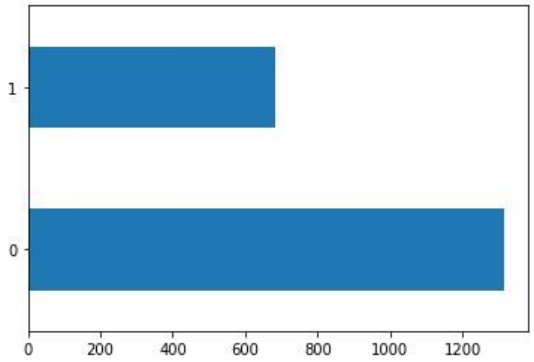


Figure 3 shows the sample density of healthy and diabetic patients in the extended Pima dataset. There are 1316 healthy and 684 diabetic patients in this data set.

Figure 4.

Density Display of Outcome Values of First Version Pima Dataset (768 samples).

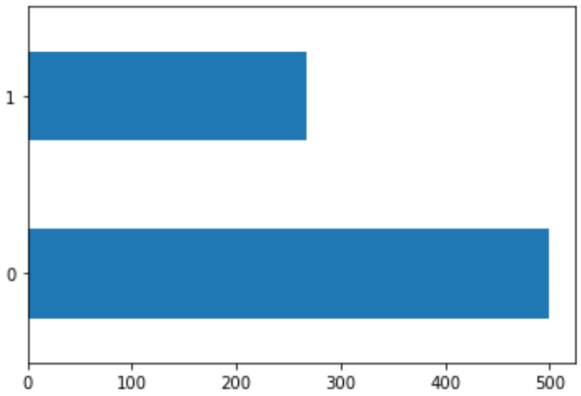
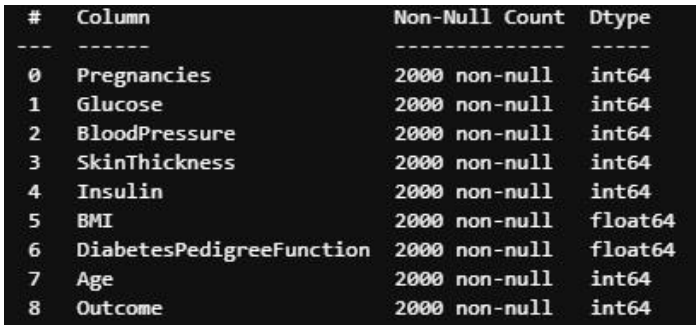


Figure 4 shows the sample density of healthy and diabetic patients in the extended Pima dataset. There are 500 healthy and 268 diabetic patients in this data set.

Figure 5.

Index of Extended Pima Dataset (2000 samples).



#	Column	Non-Null Count	Dtype
0	Pregnancies	2000 non-null	int64
1	Glucose	2000 non-null	int64
2	BloodPressure	2000 non-null	int64
3	SkinThickness	2000 non-null	int64
4	Insulin	2000 non-null	int64
5	BMI	2000 non-null	float64
6	DiabetesPedigreeFunction	2000 non-null	float64
7	Age	2000 non-null	int64
8	Outcome	2000 non-null	int64

In this dataset, 1316 of 2000 patients are healthy, and 684 are Type 2 diabetes patients. Statistical measurements used for the extended Pima data sets are given in Table 5. In the table Mean, Standard deviation, and maximum values of each attribute are given. Figure 5 shows the data type of the input and output values in the data set.

Arithmetic Mean Value (Mean)

It is a "mean" number divided by the sum of all data points in the data set divided by the total data point (Reis 2019). Equation (1) shows Mean Value Formula.

$$\bar{x} = \frac{\sum x}{N} \ (N \ equal \ to \ number \ of \ data) \qquad (1)$$

Standard Deviation (STD. DEV)

The method that measures the proximity and compliance of observations in a data set is called standard deviation. It allows us to understand how the numbers in the data group spread according to the arithmetic mean (Shi et al., 2020). Equation (2) shows the Standard Deviation Formula.

$$S = \sqrt{\frac{\sum(x-\bar{x})^2}{n-1}} \qquad (2)$$

In order to find the standard deviation value of this data set, we need to follow the steps below in order.

1. Find the Mean value of the data set.
2. The distance between each data point and the Mean value is calculated.
3. The square of the distance values is found
4. The squares of the differences are added together.
5. The resulting sum is divided by one minus the number of elements of the series.
6. The square root of the number which they found is taken.

The standard deviation tells us how near the data is to the mean. The data are spread close to the mean when the standard deviation is minimal. In contrast, a big standard deviation indicates that the data are dispersed widely from the mean. The standard deviation will be zero if all values are the same (Feng et al., 2019).

Correlation score

Correlation score is the relationship between the variables. It is a statistical method that provides information about the direction and severity of this relationship. The degree of relationship between two or more variables is examined by "Correlation Score". The correlation coefficient is a coefficient that shows the strength and direction of the relationship between the dependent variable and the independent variables. The correlation coefficient is the measure of the linear relationship between two variables and is independent of the units of the variables studied and is between $-1 \leq r \leq 1$. When the correlation coefficient approaches 0, it indicates the existence of a weak relationship between the variables. If the variables increase or decrease together, there is a positive relationship, and if one variable increases while the other decreases, there is a negative relationship. As seen in Table 7, the glucose value is the feature with the highest correlation score in the data set. The correlation score of the glucose variable is 0.458421302. The second highest correlation score is the body mass index variable. The body mass index variable correlation score is 0.276725539. The last and third most important input is the age variable. The correlation score of the age variable is 0.236509247. This value shows that the most important input value needed in the diagnosis phase is the glucose variable. The lowest variable with the correlation score in the data set is diastolic blood pressure. The correlation score of the diastolic blood pressure variable is 0.075958084.

Simulation of T2FNN System

In this study, a diabetes diagnosis system with T2FNN architecture is presented using two different versions of Pima dataset. Diabetes is a common disease that causes many fatal diseases.

Diabetes mellitus, popularly known as diabetes mellitus, is a chronic disease that occurs as a result of insufficient production of the hormone insulin, which regulates sugar in the blood. Type 2 diabetes can continue for life. If diabetes is brought under control at an early stage, life can be continued only with the use of pills. For some severe diabetes patients, using the pill may be insufficient. In case of insufficient pill use, external insulin hormone supplementation may be required. If the blood sugar measured in fasting or satiety is above the normal level, there may be diabetes mellitus.

Frequent urination, constant thirst, sudden weakness, blurred vision, constant fatigue and non-healing wounds can be a sign of diabetes. Type 2 diabetes usually occurs in adults. Nowadays, as a result of the rapid increase in obesity, type 2 diabetes has started to appear at an early age. Patients can control their sugar by controlling their diet, exercising regularly, taking medication or insulin. People with type 2 diabetes may develop serious conditions that can even lead to death if early diagnosis and treatment is not made. Millions of people around the world live with Type 2 diabetes without even knowing their disease or without adequate medical care.

When the principles of treatment in diabetes are not followed, failure to control blood sugar creates health problems in the short or long term. Diabetes can cause damage to nerves as well as vessels. These injuries are defined as complications. Acute and chronic complications of diabetes can be seen in individuals with both Type 1 and Type 2 diabetes.

Factors affecting diabetes are divided into two as genetic and environmental. Some of the factors that trigger type 2 diabetes are obesity, family history of diabetes, advanced age, sedentary life, constant stress and gestational diabetes.

The positive side of diabetes is that it is a disease that responds very well to treatment. After the diagnosis of diabetes, it is possible for patients who comply with the requirements of their treatment, have regular check-ups, receive diabetes education and adapt their lifestyle, to lead a normal and productive life.

The purpose of diabetes treatment; It is to keep your blood sugar and other risk factors (such as cholesterol and blood pressure) under control and not to allow the

formation of chronic diseases in the long term. The extent to which you can be successful depends on your age, weight, diet and exercise habits, work schedule, previous health problems, type of diabetes, and patience and determination. For the diabetic, this means constantly monitoring blood sugar levels, restricting certain foods, losing weight, and taking insulin via medication and/or injection.

Treatment of type 2 diabetes includes medical nutrition therapy, lifestyle modification, and exercise, as well as the use of oral antidiabetic drugs, usually aimed at increasing the sensitivity of cells to insulin hormone or directly increasing the release of insulin hormone. However, some people with Type 2 diabetes need insulin to keep their blood sugar stable. In these cases, treatment is supported with insulin injections at appropriate doses.

We used the first version of the Pima dataset of 768 patients and the second version of the Pima dataset of 2000 patients to test our T2FNN model (Dataset of diabetes. https://www.kaggle.com/johndasilva/diabetes).

For the diabetes diagnosis system, we used the T2FNN model we developed. Both datasets have 8 inputs and 2 ouputs. Our inputs are pragnancies, glucose, blood pressure, skinfold thinness, insulin, body mass index, diabetes pedigree function and age. Our outputs are healthy or diabetes.

Among the inputs in our data set, the input with the highest correlation score is the glucose value. The correlation score of the Glucose value was calculated as 0.45. The two entries with the lowest correlation scores are skin thicknes and blood pressure. The correlation score of skin thicknes and blood pressure values is 0.07.

The first entry in the datasets is how many pregnancies the patient had. If the patient has not been pregnant or is male, this value should be zero. People who have had 4 or more pregnancies or have given birth have a higher risk of diabetes.

The second input to the system is the 2-hour glucose value. A 2-hour glucose value above 140 creates a risk of diabetes.

The third entry in the datasets is the person ‘s blood pressure value. High blood pressure increases the risk of diabetes. In healthy people, blood pressure is below 90.

The fourth entry in the dataset is skin thickness. It has been observed that the skin thickness increases in people with diabetes. Therefore, people with diabetes have greater skinfold thickness. In healthy individuals, the skinfold thickness was found to be 15 mm on average. In people with diabetes, the skinfold thickness is over 23 mm.

The fifth entry in the datasets is the 2-hour serum insulin value. In healthy people, the serum insulin value is below 166. A 2-hour serum insulin value above 166 creates a risk of diabetes.

The sixth entry in our datasets is the body mass index. Having a higher body mass index indicates that you have a higher body weight than your height, in other words, you are fat. In healthy people, the body mass index is below 30. A body mass index above 30 creates a risk of diabetes.

The seventh entry in the datasets is the diabetes pedigree function. Diabetes also occurs due to genetic reasons, so a family history of diabetes increases the risk of the disease. In healthy individuals, the diabetes pedigree function value is below 0.5. Diabetes pedigree function value over 0.5 creates diabetes risk.

The last entry in the datasets used in this study is age. Type 2 diabetes is not a congenital disease. Type 2 diabetes can often be seen in unhealthy and sedentary living conditions.

Today, one of the most important factors triggering diabetes is obesity. Type 2 diabetes usually occurs in later ages, although it is now seen at younger ages due to obesity.

In the data sets we use, there are 2 outputs in response to all these inputs. In response to all these inputs, we can get two different results in the data sets as healthy or diabetic. All the inputs in the datasets we used in our study are values representing diabetes symptom.

Simulation Results of T2FNN system

The first version of the Pima dataset has a total of 768 samples. Of 768 samples, 265 have diabetes and 500 are healthy. In the new version of the Pima dataset, which consists of 2000 samples, there are 684 samples of diabetes patients and 1316 samples of healthy people.

In Table 4 and Table 5, some examples of statistical data from the Pima datasets are presented. In Table 4, some examples of statistical data from the old version of the Pima dataset are presented.

Statistical results for the new version of the Pima dataset are given in Table 5. Statistical results of the old version of Pima dataset consisting of 768 samples are given in Table 4. In Table 4 and Table 5, the mean, standard deviation and maximum values of the attributes in the data sets are presented.

Since diabetes is a complex disease, the relationship between input and output values is not highly linear. We used the correlation score to better understand the Relationship between the data. The correlation score indicates that when the value of one variable changes, the other variable will also change in a certain direction according to the relationship between them. Since correlation is a powerful measurement method that is not affected by unit differences, it allows to measure and compare not only the direction of the relationship but also the strength of the relationship, unlike covariance.

The correlation score shows the most important inputs used to produce the outputs. The correlation score assigns points based on how important the input signals are to predict a target variable. In this study, we used a statistical correlation score to determine the significance of the inputs used in the datasets. In Table 6, we present the correlation score of the first version of the Pima dataset. As seen in Table 6, there is not a big difference between the correlation scores of our inputs. The highest correlation score belongs to the glucose entry. Skin thickness and blood pressure inputs presented the lowest correlation score. In addition, the correlation score results of the new version of the Pima dataset are shown in Table 7. The correlation scores of the Pima dataset are close to the old version of the Pima dataset.

In this study, T2FNN, an integrated working model of Type-2 fuzzy logic and neural network, was used for the diagnosis of diabetes.

The main problem in the design of the presented system was to find suitable values for the parameters of the antecedent and the concluding parts of the type-2 fuzzy rules in equation (1).

These are c1ij, c2ij centers and σij widths of membership functions and wij and vjk coefficients of the linear functions and output layer correspondingly.

In this study, gradient descent algorithm and cross validation methods were applied to adjust the parameters used in the presented T2FNN model. Simulation results in both data sets used were obtained by 10-fold cross-validation technique for 2000 epochs.

Table 2.

Fragment from the First Version of Pima Dataset (768 samples).

Pregnancies	Glucose	Blood Pressure	Skinfold Thickness	Insulin	BMI	DP	Age	Outcome
3	169	74	19	125	29,9	0,268	31	1
7	142	90	24	480	30,4	0,128	43	1
7	129	68	49	125	38,5	0,439	43	1
2	121	70	32	95	39,1	0,886	23	0
2	129	74	26	205	33,2	0,591	25	0
1	144	82	46	180	46,1	0,335	46	1
1	140	74	26	180	24,1	0,828	23	0
2	56	56	28	45	24,2	0,332	22	0
1	112	80	45	132	34,8	0,217	24	0
1	112	80	45	132	34,8	0,217	24	0
9	145	80	46	130	37,9	0,637	40	1

Table 3.

Fragment from extended version of Pima dataset (2000 samples).

Pregnan-cies	Gluco-se	Blood Pressure	Skinfold Thickness	Insulin	BMI	DP	Age	Outcome
0	84	82	31	125	38,2	0,233	23	0
0	135	68	42	250	42,3	0,365	24	1
1	139	62	41	480	40,7	0,536	21	0
0	173	78	32	265	46,5	1,159	58	0
2	83	65	28	66	36,8	0,629	24	0
4	125	70	18	122	28,9	1,144	45	1
2	81	72	15	76	30,1	0,547	25	0
7	195	70	33	145	25,1	0,163	55	1
6	154	74	32	193	29,3	0,839	39	0
2	117	90	19	71	25,2	0,313	21	0
0	180	90	26	90	36,5	0,314	35	1

Table 4.

Statistical Measurements for First Version of the PIMA Dataset.

Attributes	mean	std	max
Pregnancies	3.845052	3.369578	17.00
Glucose	120.894531	31.972618	199.00
Blood Pressure	69.105469	19.355807	122.00
Skin Thickness	20.536458	15.952218	99.00
Insulin	79.799479	115.244002	846.00
BMI	31.992578	7.884160	67.10
Diabetes Pedigree Function	0.471876	0.331329	2.42
Age	33.240885	11.760232	81.00
Outcome	0.348958	0.476951	1.00

Table 5.

Statistical Measurements for the Extended PIMA Dataset.

	mean	std	max
Pregnancies	3.70350	3.306063	17.00
Glucose	121.18250	32.068636	199.00
Blood Pressure	69.14550	19.188315	122.00
Skin Thickness	20.93500	16.103243	110.00
Insulin	80.25400	111.180534	744.00
BMI	32.19300	8.149901	80.60
Diabetes Pedigree Function	0.47093	0.323553	2.42
Age	33.09050	11.786423	81.00
Outcome	0.34200	0.474498	1.00

Table 6.

Correlation Scores of the Input features for the First Version Pima Dataset (768 samples)

Input Variable	Correlation Scores
Glucose	0,466581398
BMI	0,292694663
Age	0,238355983
Pregnancies	0,221898153
Diabetes Pedigree Function	0,173844066
Insulin	0,130547955
Skin Thickness	0,074752232
Blood Pressure	0,06506836

Table 7.

Correlation Scores of the Input Features for the Extended Pima Dataset (2000 samples).

Input Variable	Correlation Scores
Glucose	0,458421302
BMI	0,276725539
Age	0,236509247
Pregnancies	0,224436993
Diabetes Pedigree Function	0,155459079
Insulin	0,120923622
Skin Thickness	0,076040247
Blood Pressure	0,075958084

Two versions of the Pima dataset were tested for the simulation results. Each data set used was divided into 10 equal groups. The obtained 9 groups were used for training. The remaining 1 group was used for testing. In each epoch, the number of test group will change. During the simulation process, we used different number of rules for the design of the presented system.

Root mean square error (RMSE), accuracy, sensitivity, specificity and precision results were used to measure the performances of the presented system. Simulations were made using 16, 32, 40, 48, 64, 80, 100 fuzzy rules. Learning of the 80 and 100 rule type-2 fuzzy TSK system is accordingly shown in Figure 6(a) and Figure 6(b). Figures 7(a) and 7(b) show graphical representations of type 2 membership functions of the T2FNN system before (randomly initialized) and after training, respectively.

Only four membership functions are specified to present an understandable figure. Learned membership functions are used to define the antecedent part of type-2 fuzzy rules. The concluding part of the rules uses linear functions characterized by their weighting coefficients. T2FNN with trained c1, c2, o and w values is used for classification of diabetes in online mode.

Table 8 shows the simulation results of the T2FNN system for diabetes diagnosis using different number of rules. The simulation results presented in Table 8 were obtained with the new version of the Pima dataset consisting of 2000 patients.

Table 9 shows the simulation results of the T2FNN system for diagnosing diabetes using a different number of rules. The simulation results presented in Table 9 were obtained with the old version of the Pima dataset consisting of 768 patients. As shown in Table 8 and Table 9, the higher the number of fuzzy rules, the higher the system accuracy. When both data sets were tested with the T2FNN model presented in this study, the best results were obtained with 100 fuzzy rules.

Training, validation and test errors obtained with the new version of Pima dataset consisting of 2000 samples are 0.185, 0.219 and 0.217, respectively.

Accuracy, sensitivity, specificity and precision values were obtained as 99.75, 100, 99.6 and 99.27, respectively.

Training, validation and testing errors obtained with the old version of Pima dataset consisting of 768 samples were 0.229, 0.251 and 0.239, respectively.

Accuracy, sensitivity, specificity and precision values were obtained as 99.06, 99.24, 99.00 and 98.13, respectively.

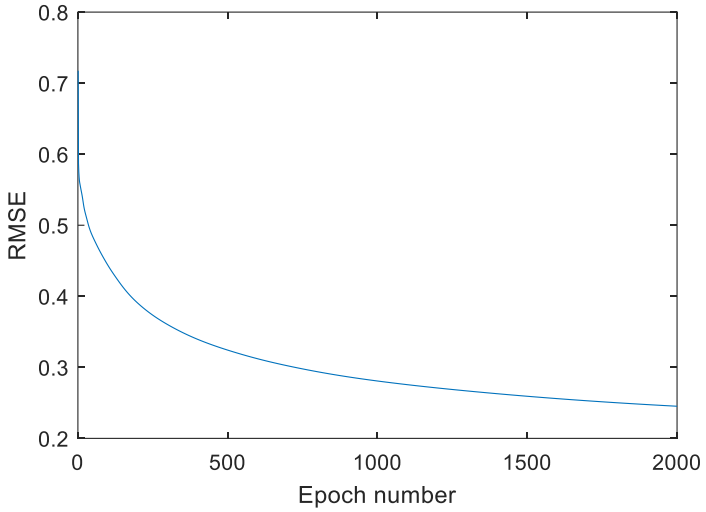
In order to show the effectiveness of the T2FNN model presented in this study, the simulation results were compared with other results in the literature. In all the studies in the literature, the first version of the Pima dataset consisting of 768 patients was used. For a fair comparison, we present our results with the old version of the Pima dataset in Table 11. In Table 9, the simulation results obtained with the first

version of the pima dataset are presented. The simulation results were obtained using a different number of rules. The simulation results obtained from both data sets in Table 8 and Table 9 are presented with rule numbers of 16, 32, 40, 48, 64, 80, 100.

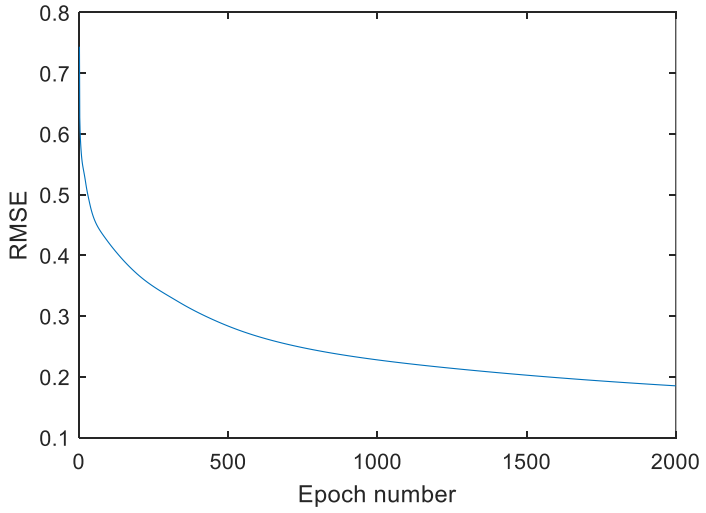
In the design phase of the presented system, gradient descent algorithm, T2FNN structure and cross validation technique were used. Table 8 shows the simulation results of the T2FNN system using the extended PIMA dataset. Table 9 shows the simulation results of the T2FNN system using the first PIMA dataset.

Figure 6.

Learning: (a) 80 Rules, (b) 100 Rules.



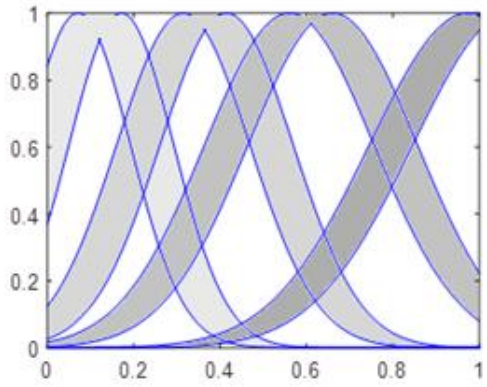
(a)



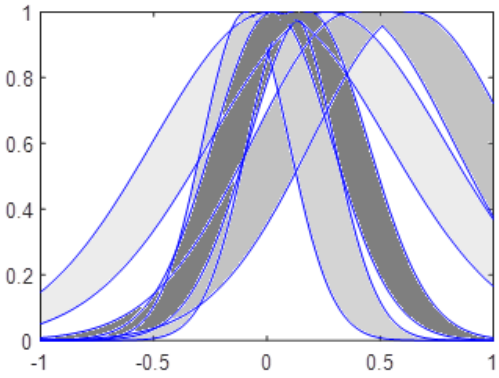
(b)

Figure 7.

Graphical illustration of membership functions before training (a) and after training (b).



(a)



(b)

Table 8.

T2FNN Simulation Results using Extended PIMA Datasets (2000 Data Samples).

No	Training Error	Evaluation Error	Test Error	Accuracy	Sensitivity	Specificity	Precision
16	0.528336	0.528133	0.527380	0.806000	0.769091	0.82000	0.618421
32	0.454794	0.454406	0.452687	0.870000	0.850993	0.878223	0.751462
40	0.416043	0.415256	0.414421	0.903000	0.913851	0.898438	0.790936
48	0.394395	0.393396	0.391265	0.924500	0.914463	0.929256	0.859649
64	0.325452	0.322762	0.325419	0.959000	0.954683	0.961136	0.923977
80	0.245239	0.253867	0.250115	0.991000	0.986842	0.993161	0.986842
100	0.185096	0.219340	0.217188	0.997500	1.000000	0.996215	0.992690

Table 9.

Simulation Results using Old Version of PIMA Diabetes Datasets (768 data samples)

No	Training Error	Evaluation Error	Test Error	Accuracy	Sensitivity	Specificity	Precision
16	0.519818	0.522744	0.519274	0.825545	0.804545	0.878788	0.761194
32	0.479357	0.481281	0.476428	0.869792	0.85000	0.878788	0.761194
40	0.431486	0.433478	0.427994	0.904948	0.904564	0.905123	0.813433
48	0.394739	0.397052	0.391065	0.924479	0.944915	0.915414	0.832090
64	0.347143	0.359279	0.352994	0.955729	0.930147	0.969758	0.944030
80	0.299493	0.302788	0.306103	0.968750	0.984127	0.961240	0.945372
100	0.229231	0.251533	0.239876	0.990685	0.992453	0.990060	0.981343

Comparatıve Results

In this study, we obtained results with 12 different machine learning algorithms as the first step for the diabetes disease classification problem. In the literature, it is seen that machine learning algorithms are frequently used in classification problems. We first got results with 12 different machine learning algorithms to classify diabetes. In Table 10, we obtained results with 12 different machine learning algorithms using Pima dataset to classify Type-2 diabetes. As seen in Table 10, the results obtained with machine learning algorithms could not provide sufficient accuracy. Since diabetes is a complex disease, the data set obtained is also very complex. Fuzzy logic approach has always offered higher accuracy in such datasets where uncertainties are very high. Especially the Type-2 interval fuzzy logic approach can handle such problems very well. For this reason, T2FNN model is presented in this study.

Table 11 presents the comparative simulation results of different methods found in the literature.

In this study, we presented the results obtained with our T2FNN model with 16, 32, 40, 48, 64, 80 and 100 rules. Considering the results obtained in the presented T2FNN model, the T2FNN model with 100 rules presented the highest accuracy. In both data sets used, the highest accuracy was obtained with the T2FNN model with 100 rules. The T2FNN model presented in this study was compared with the studies in the literature. It has been shown that the T2FNN model can be used effectively for the diagnosis of diabetes.

Table 10.

The results we obtained with machine learning algorithms.

Method	Accuracy
Light Gradient Boosting Machines	0,8316
Random Forest	0,9283
XGBoost Machines	0,8733
CART	0,8200
CatBoost Machines	0,9050
KNN	0,9428
Gradient Boosting Machines	0,8433
ANN	0,7966
RBF SVC	0,8133
SVC	0,7933
Gaussian Naïve Bayes	0,773
Logistic Regression	0,7933

Table 11.

Comparative Results of Different Models using PIMA Diabetes (768 samples)

Authors	Methodology	Accuracy
Choubey and Paul	MLP NN	0.79
Polat et al.	SVM	0,79
Beloufa and Fayssal	Artificial Bee Colony	0,84
Bashir et al.	HM-BagMoov	0,86
Bozkurt et al.	ANN	0.76
Tand and Tseng	Genetic Algorithm	0.81
Aslam et al.	3 Steps Genetic programming	0.87
Nabi et al.	4 Machine Learning Combination	0.80
Maniruzzaman et al.	Quadratic Discriminant Analysis	0.82
Mercaldo et al.	Deep Learning	0.77
Rabina and Chopra	Multi-Layer Perceptron	0.77
Sreedevi and Padmavathamma	Genetic Algorithm	0.72
Sa ‘ddi et al.	Naïve Bayes	0.76
Current research	T2FNN (32 rules)	0.87
Current research	T2FNN (80 rules)	0.969
Current research	T2FNN(100 rules)	0.991

CHAPTER V

Conclusion

The type-2 Fuzzy neural network system is proposed for diagnosis of diabetes. The design of proposed system is based on statistical data taken from physician doctors.

Analysis of existing diagnostic systems show that the process of diagnosis of diabetes is very complex, requires a high level of expertise. These systems use input symptoms and signs for the diabetes diagnosis. In many cases the medical data chracterising the input symtoms has a noisy character and charctersied uncertainty and imprecision. In such cases one of appropriate methodologies used for diagnosing diabetes is the use of fuzzy sets theory.

The high level of uncertainty in the medical data requires the use of type-2 fuzzy set theory in handling these uncertainties. The integration of the Type-2 Fuzzy Logic and Artificial Neural Networks is proposed for the designing diagnostic system of diabetes.

The structure of T2FNN system for diagnosis of diabetes has been developed. The T2FNN structure is based on TSK type fuzzy rules. The presented structure uses the neural network learning capability for implementation fuzzy reaosning process.

Using a gradient descent the learning algorithm of T2FNN is presented. The design stages of the T2FNN system is presented for diagnosis of diabetes.

The designed T2FNN is used for the diagnosis of diabetes. The two diabetes databases are used for the designing of diagnostic system. The first one is Pima dataset and second one is the extended diabetes data sets.

The simulation of T2FNN system for diagnosis of diabetes has been performed and the performance characteristics of the designed systems have been obtained through simulations. Comparative results are provided in order to evaluate the efficiency of the proposed T2FNN system.

The obtained simulation results indicate the efficiency of constructed T2FNN based diagnostic system. The proposed T2FNN based diagnostic system is designed in Matlab pasckage. Comperative results have been done in order to demonstrate efficiency of the proposed T2FNN based diagnostic system.

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APPENDICES

Appendix A

Ethical Approval Documents

Since the datasets used in this thesis are public, there is no ethical approval document that can be presented.

Prof. Dr. Rahib Abiyev
Supervisor

Appendix B

Learning Methods

The design of the type-2 FNS includes the determination of the unknown parameters that are the parameters of the antecedent and the consequent parts of the fuzzy if-then rules (3). In the antecedent parts, the input space is divided into a set of fuzzy regions, and in the consequent parts the system behavior in those regions is described. In this thesis, the gradient algorithm is applied in order to train and determine the parameters of the antecedent and the consequent parts, that is the parameters of the membership functions $c1_{ij}$, $c2_{ij}$ and σ_{ij} ($i=1,..,m$, $j=1,..,n$) in the second layer and the parameters of the linear functions w_{ij}, b_j ($i=1,..,m$, $j=1,..,n$) in the fourth layer(Abiyev & Kaynak, 2010).

At the first step, the output error is calculated.

$$E = \frac{1}{2}\sum_{i=1}^{O}(u_i^d - u_i)^2 \tag{7}$$

Here O is number of output signals of the network (in the given case O=1), u_i^d and u_i are the desired and the current output values of the network, respectively. The parameters w_{ij}, b_j ($i=1,..,m$, $j=1,..,n$) and $c1_{ij}, c2_{ij}$ and σ_{ij} ($i=1,..,m$, $j=1,..,n$) are adjusted using the following formulas.

$$w_{ij}(t+1) = w_{ij}(t) - \gamma\frac{\partial E}{\partial w_{ij}};\ b_j(t+1) = b_j(t) - \gamma\frac{\partial E}{\partial b_j} \tag{8}$$

$$c1_{ij}(t+1) = c1_{ij}(t) - \gamma\frac{\partial E}{\partial \underline{c}_{ij}};\ c2_{ij}(t+1) = c2_{ij}(t) - \gamma\frac{\partial E}{\partial \bar{c}_{ij}} \tag{9}$$

$$\sigma_{ij}(t+1) = \sigma_{ij}(t) - \gamma\frac{\partial E}{\partial \sigma_{ij}} \tag{10}$$

Here γ is the learning rate, m is the number of input signals of the network (input neurons) and n is the number of rules (hidden neurons), $i=1,..,m$, $j=1,..,n$. The derivatives in (10) are determined by the following formulas.

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial u}\frac{\partial u}{\partial y_j}\frac{\partial y_j}{\partial w_{ij}} = (u(t)-u^d(t))\cdot\left(\frac{q\cdot \underline{f}_j}{\sum_{j=1}^{n}\underline{f}_j} + \frac{(1-q)\cdot \overline{f}_j}{\sum_{j=1}^{n}\overline{f}_j}\right)\cdot x_i \text{, j=1,..,n} \quad (11)$$

$$\frac{\partial E}{\partial b_j} = \frac{\partial E}{\partial u}\frac{\partial u}{\partial y_j}\frac{\partial y_j}{\partial b_j} = (u(t)-u^d(t))\cdot\left(\frac{q\cdot \underline{f}_j}{\sum_{j=1}^{n}\underline{f}_j} + \frac{(1-q)\cdot \overline{f}_j}{\sum_{j=1}^{n}\overline{f}_j}\right), \text{ j=1,..,n} \quad (12)$$

The derivatives in (11,12) are determined by the following formulas.

$$\frac{\partial E}{\partial \sigma_{ij}} = \sum_j \frac{\partial \mathrm{E}}{\partial u}\left(\frac{\partial u}{\partial \underline{f}_j}\frac{\partial \underline{f}_j}{\partial \underline{\mu}_{ij}}\frac{\partial \underline{\mu}_{ij}}{\partial \sigma_{ij}} + \frac{\partial u}{\partial \overline{f}_j}\frac{\partial \overline{f}_j}{\partial \overline{\mu}_{ij}}\frac{\partial \overline{\mu_j}}{\partial \sigma_{ij}}\right) \quad (13)$$

$$\frac{\partial E}{\partial c1_{ij}} = \sum_j \frac{\partial \mathrm{E}}{\partial u}\left(\frac{\partial u}{\partial \underline{f}_j}\frac{\partial \underline{f}_j}{\partial \underline{\mu}_{ij}}\frac{\partial \underline{\mu}_{ij}}{\partial c1_{ij}} + \frac{\partial u}{\partial \overline{f}_j}\frac{\partial \overline{f}_j}{\partial \overline{\mu}_{ij}}\frac{\partial \overline{\mu}_{ij}}{\partial c1_{ij}}\right);$$

$$\frac{\partial E}{\partial c2_{ij}} = \sum_j \frac{\partial \mathrm{E}}{\partial u}\left(\frac{\partial u}{\partial \underline{f}_j}\frac{\partial \underline{f}_j}{\partial \underline{\mu}_{ij}}\frac{\partial \underline{\mu}_{ij}}{\partial c2_{ij}} + \frac{\partial u}{\partial \overline{f}_j}\frac{\partial \overline{f}_j}{\partial \overline{\mu}_{ij}}\frac{\partial \overline{\mu}_{ij}}{\partial c2_{ij}}\right) \quad (14)$$

Here

$$\frac{\partial E}{\partial u} = u(t)-u^d(t);\ \frac{\partial u}{\partial \underline{f}_j} = q\frac{y_j-\underline{u}}{\sum_{j=1}^{n}\underline{f}_j};\ \frac{\partial u}{\partial \overline{f}_j} = (1-q)\frac{y_j-\overline{u}}{\sum_{j=1}^{n}\overline{f}_j};\ \underline{u} = \frac{\sum_{j=1}^{n}\underline{f}_j y_j}{\sum_{j=1}^{n}\underline{f}_j};\ \overline{u} = \frac{\sum_{j=1}^{n}\overline{f}_j y_j}{\sum_{j=1}^{n}\overline{f}_j} \quad (15)$$

If we use t-norm *prod* operator, then

$$\frac{\partial \underline{f}_j}{\partial \underline{\mu}_{ij}} = \prod_{\substack{k=1\\k\neq i}}^{N1}\underline{\mu}_{kj};\ \frac{\partial \overline{f}_j}{\partial \overline{\mu}_{ij}} = \prod_{\substack{k=1\\k\neq i}}^{N1}\overline{\mu}_{kj};\ i=1,..,\mathrm{N1},\ k=1,..,\mathrm{N1},\ j=1,..,\mathrm{N2} \quad (16)$$

Upper and lower membership functions between i-th input and j-th hidden neurons of layer 3 can be written as follows (see fig.1(b)):

$$\underline{\mu}_{ij}(x)=\begin{cases} G(c2_{ij},\sigma_{ij},x_i), & x_i \le \dfrac{c1_{ij}+c2_{ij}}{2} \\ G(c1_{ij},\sigma_{ij},x_i), & x_i > \dfrac{c1_{ij}+c2_{ij}}{2} \end{cases} ; \bar{\mu}_{ij}(x)=\begin{cases} G(c1_{ij},\sigma_{ij},x_i), & x_i < c1_{ij} \\ 1, & c1_{ij} \le x_i \le c2_{ij} \\ G(c2_{ij},\sigma_{ij},x_i), & x_i > c2_{ij} \end{cases} \quad (17)$$

Here $G(c_{ij},\sigma_{ij},x_i)$ is determined as

$$G(c_{ij},\sigma_{ij},x_i)=\exp(-\frac{1}{2}\frac{(x_i-c_{ij})^2}{\sigma_{ij}^2}) \quad (18)$$

Then

$$\frac{\partial \bar{\mu}_j(x_i)}{\partial c1_{ij}}=\begin{cases} G(c1_{ij},\sigma_{ij},x_i)\dfrac{(x_i-c1_{ij})}{\sigma_{ij}^2}, & x_i < c1_{ij} \\ 0, & c1_{ij} \le x_i \le c2_{ij} \\ 0, & x_i > c2_{ij} \end{cases};$$

$$\frac{\partial \underline{\mu}_j(x_i)}{\partial c1_{ij}}=\begin{cases} 0, & x_i \le \dfrac{c1_{ij}+c2_{ij}}{2} \\ G(c1_{ij},\sigma_{ij},x_i)\dfrac{(x_i-c1_{ij})}{\sigma_{ij}^2}, & x_i > \dfrac{c1_{ij}+c2_{ij}}{2} \end{cases} \quad (19)$$

$$\frac{\partial \bar{\mu}_j(x_i)}{\partial c2_{ij}}=\begin{cases} 0, & x_i < c1_{ij} \\ 0, & c1_{ij} \le x_i \le c2_{ij} \\ G(c2_{ij},\sigma_{ij},x_i)\dfrac{(x_i-c2_{ij})}{\sigma_{ij}^2}, & x_i > c2_{ij} \end{cases};$$

$$\frac{\partial \underline{\mu}_j(x_i)}{\partial c2_{ij}}=\begin{cases} G(c2_{ij},\sigma_{ij},x_i)\dfrac{(x_i-c2_{ij})}{\sigma_{ij}^2}, & x_i < \dfrac{c1_{ij}+c2_{ij}}{2} \\ 0, & x_i \ge \dfrac{c1_{ij}+c2_{ij}}{2} \end{cases} \quad (20)$$

$$\frac{\partial \bar{\mu}_j(x_i)}{\partial \sigma_{ij}} = \begin{cases} G(c1_{ij}, \sigma_{ij}, x_i) \dfrac{(x_i - c1_i)^2}{\sigma_{ij}^3}, & x_i < c1_{ij} \\ 0, \quad c1_{ij} \le x_i \le c2_{ij} \\ G(c2_{ij}, \sigma_{ij}, x_i) \dfrac{(x_i - c2_{ij})^2}{\sigma_{ij}^3}, & x_i > c2_{ij} \end{cases};$$

$$\frac{\partial \underline{\mu}_j(x_i)}{\partial \sigma_{ij}} = \begin{cases} G(c2_{ij}, \sigma_{ij}, x_i) \dfrac{(x_i - c2_{ij})^2}{\sigma_{ij}^3}, & x_i \le \dfrac{c1_{ij} + c2_{ij}}{2} \\ G(c1_{ij}, \sigma_{ij}, x_i) \dfrac{(x_i - c1_{ij})^2}{\sigma_{ij}^3}, & x_i > \dfrac{c1_{ij} + c2_{ij}}{2} \end{cases} \quad (21)$$

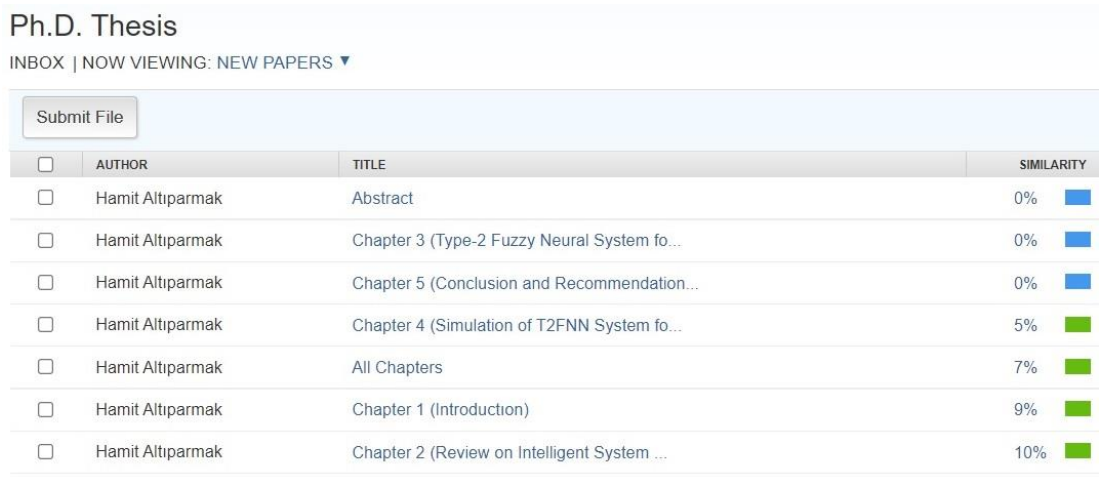
The parameters of the type-2 FNS can thus be updated using (10)-(12) together with (13)-(22).

As mentioned above, the parameter q in (6) enables to adjust the lower or the upper portions in the final output. During learning the value of q is optimized using

$$q(t+1) = q(t) - \gamma \frac{\partial E}{\partial q}; \text{ Here } \frac{\partial E}{\partial q} = (u - u^d) \left(\frac{\underline{f}_j}{\sum_{j=1}^{n} \underline{f}_j} - \frac{\bar{f}_j}{\sum_{j=1}^{n} \bar{f}_j} \right); \quad (22)$$

Appendix C

Turnitin Similarity Report



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Prof. Dr. Rahib Abiyev

Supervisor

Appendix D

Curriculum Vitae

PERSONAL INFORMATIONS

Surname, Name: Altıparmak, Hamit

Date of Birth: 10 April 1989

Place of Birth: Nicosia, Cyprus

EDUCATION

Degree	Department/Program	University	Year of Graduation
M.Sc.	Computer Engineering	Near East University	2017
B.Sc.	Computer Engineering	Near East University	2014

Master Thesis Title: Diabetes Diagnoses System By Using VP Expert System.

WORK EXPERIENCE

Title	Place	Year
Lecturer	NEU, Faculty of Engineering, Department of Computer Engineering	2017-present
Research Assistant	NEU, Faculty of Engineering, Department of Computer Engineering	2014-2017

FOREIGN LANGUAGES

Fluent spoken and written English

PUBLICATIONS IN INTERNATIONAL REFERED JOURNALS AND CONFERENCES

- Abiyev, R. H., & **Altiparmak, H.** (2021). Type-2 Fuzzy Neural System for Diagnosis of Diabetes. Mathematical Problems in Engineering, 2021.
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