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Artificial intelligence–based neural network for the diagnosis of diabetes and COVID: ANN model with optimum predictor variable

Dr. Gilbert Roland
Department of Health Studies, Astrialearning Consortium of Universities, 100 S. Ashley Drive Suite 600, Tampa, FL 33602 USA.
Email: gilbert@astrialearning.org
ORCID: https://orcid.org/0000-0001-5448-7027"

Dr Navin Kumar
Associate professor, Department of community medicine, Narayan medical college and hospital
Sasaram, Bihar
Corresponding author email: drnavinkr1998@gmail.com

Dr. Bharathi Gururaj
Associate Professor, Department of Electronics and Communication Engineering ACS college of Engineering, Bangalore 560074
bharathigururaj@gmail.com

Dr Richa
Principal, Government Leather Institute, Uttar Pradesh, India,
Email: vermaricha29@gmail.com

Dr. Sunil Devidas Bobade
New Horizon Institute of Technology and Management, Thane, India 400615
Email: sunilbobade@nhitm.ac.in
ORCID: 0000-0001-8650-2826

Dr Melanie Elizabeth Lourens
Deputy Dean: Faculty of Management Sciences, Durban University of Technology City, Durban, KwaZulu-Natal, South Africa
Email: Melaniel@dut.ac.za
Orcid number: 0000-0002-4288-8277"

***Abstract*---**In many nations, the prevalence of diabetes is rising, and its impact on national health cannot be overlooked. Smart medicine is a medical concept in which technology is used to aid in disease detection and treatment. The objective of this study is to take a gander

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at the information and look at changed diabetic mellitus forecasting algorithms. According to rising dismalness as of late, the quantity of diabetic patients worldwide will arrive at 642 million out of 2040, suggesting that one out of each 10persons would be affected. This worrisome figure, without a question, demands immediate attention. AI has been applied to an assortment of aspects of clinical wellbeing as a result of its rapid progress. To predict diabetes mellitus in this review, we utilized a choice tree, an arbitrary timberland, and a neural organization.

***Keywords*---**Diabetes Mellitus, Neural Network, Artificial Intelligence.

Introduction

Diabetes is a medical situation where in the glucose level in blood, routinely called as glucose, is amazingly higher. The standard wellspring of the energy is known as blood glucose, which originates from the ingestion. Insulin, a compound passed on by the pancreas, helps glucose ingestion into cells for use as energy. (Sakr 2017)A piece of the time your body doesn't elapse sufficiently adequately on enough - or any - insulin or it doesn't use it suitably. Glucose remains in your stream and doesn't show up at your cells along these lines. Having a great deal of glucose in your blood may prompt medical problems after some time. In spite of the fact that there is no remedy for diabetes, you might take endeavors to oversee it and remain sound. Diabetes is additionally alluded to as "a dash of sugar" or "marginal diabetes." These words recommend that somebody doesn't have diabetes nor has a milder type of the infection, but diabetes influences everybody.

Artificial intelligence (AI) is an expansive expression that alludes to the hypothesis and advancement of virtual frameworks that can fill roles generally performed by people, for example, vision, discourse acknowledgment, navigation, and language interpretation. It very well may be just about as straightforward as a set of rules, or it can be driven by sophisticated statistical methodologies. Simulated intelligence is a subset of man-made mental ability (AI) that licenses structures to learn and create their own without being unequivocally changed. Managed, unaided, semi-regulated, and support based AI is all choices. By copying the construction of the human cerebrum with repetitive neural organizations, a deep learning computer seeks to emulate human intelligence.

Artificial intelligence (AI) and AI (ML) strategies are widely employed in many scientific domains and are altering industries all over the world. Medical services frameworks, then again, have been delayed to fuse these developments and are a long ways behind in this area. (Association 2012)

Hyperglycemia is a side effect of diabetes mellitus, which is a constant condition. It can possibly trigger a huge number of issues. A few procedures, including the standard AI strategy (Kavakiotis et al., 2017, for example, support vector machine (SVM), Decision tree (DT), determined backslide, and others; have actually been applied to anticipate diabetes. Polat and Günes (2007) used Principal component analysis (PCA) and neural cushioned inferring to isolate diabetics from sound people. To anticipate type 2 diabetes, Yue et al. (2008) utilized the quantum behavior particle swarm (QPSO) calculation with the weighted least squares support vector machine (WLS-SVM). LDA-MWSVM is a diabetes figure approach proposed by Duygu and Esin (2011).To limit the aspects and concentrate the highlights in this framework, the researchers utilized Linear Discriminant Analysis (LDA). Razavian et al. (2015) created calculated relapse based forecast models for particular kinds of type 2 diabetes onsets to manage high-layered datasets. Georga et al. (2013) zeroed in on glucose and utilized help vector with systemic vascular resistance (SVR) as a multivariate relapse issue to anticipate diabetes. Besides, an expanding number of explores utilized group ways to deal with further develop precision (Kavakiotis et al., 2017). Ozcift and Gulten (2011) presented pivot backwoods, another outfit methodology that incorporates 30 AI draws near. Han et al. (2015) proposed an AI calculation that adjusted the SVM expectation rules.

Artificial intelligence (AI) technologies are rapidly advancing, promising to make ongoing organized also unstructured prosperity data open for the thought of PWDs. "The study of causing PCs to do things that require acumen when done by people," as per the Turing Archive for the History of Computing. 9 AI alludes to an assortment of techniques for imitating human understanding and performing different reasoning tasks, including visual wisdom, talk affirmation, investigation, independent direction, and language translation. Mental structures use an assortment of AI advancements to help people broaden and scale their insight and skill by allowing them to quickly access enormous information sources to solve challenges.

According to a 2017 survey, 68% of flexible prosperity application fashioners and distributers acknowledge diabetes will continue to be indisputably the main clinical consideration field with the best market potential for electronic prosperity game plans sooner rather than later, and 61% acknowledge AI will be the most risky development forming the high level prosperity region in the near future. Despite the way that forward leaps in AI for clinical consideration are being chronicled in the literature11 and new AI-powered devices for diabetes care are being approved,12 an efficient evaluation of clinically pertinent diabetes AI applications is inadequate. The objective of this paper is to help PWDs, their essential consideration suppliers, endocrinologists, wellbeing experts, family, and carers better understand what important AI developments are available now.

As of June 2018, the biomedical literature index has over 28 million articles and is expanding at what might be compared to almost 300 million books. Unstructured information makes up around 80% of all wellbeing information. Nonclinical information sources incorporate gadget and sensor information (regularly alluded to as Internet of Things information), genomic information, and social determinants of wellbeing information, just as clinician notes, clinical preliminaries, clinic records and release synopses, imaging and research center reports, and nonclinical information sources, for example, genomic information and social determinants of wellbeing information.

Review Of Litreature

VijiyaKumar et al. suggested the Random Forest algorithm for diabetes forecast to plan a framework that can do early diabetes expectation for a patient with more noteworthy precision utilizing AI strategies. The recommended model gives the best outcomes to diabetic forecast, and the discoveries uncover that the expectation framework is prepared to do precisely, effectively, and above all, instantaneously predicting diabetes disease. Nonso Nnamoko et al. proposed an ensemble supervised learning strategy for forecasting diabetes onset. They used five commonly used classifiers for the ensembles and a meta-classifier to combine their outputs. The findings are reported and compared to other studies in the literature that used the same dataset. It is demonstrated that diabetes onset prediction can be done more accurately utilising the proposed strategy.

Diabetes Prediction was provided by N. Joshi et al. Using Machine Learning Techniques tries to predict diabetes using three regulated AI strategies: SVM, Logistic Regression,and Artificial Neural Networks (ANN). (Grandvalet 2005)This project proposes an effective method for detecting diabetes illness earlier.

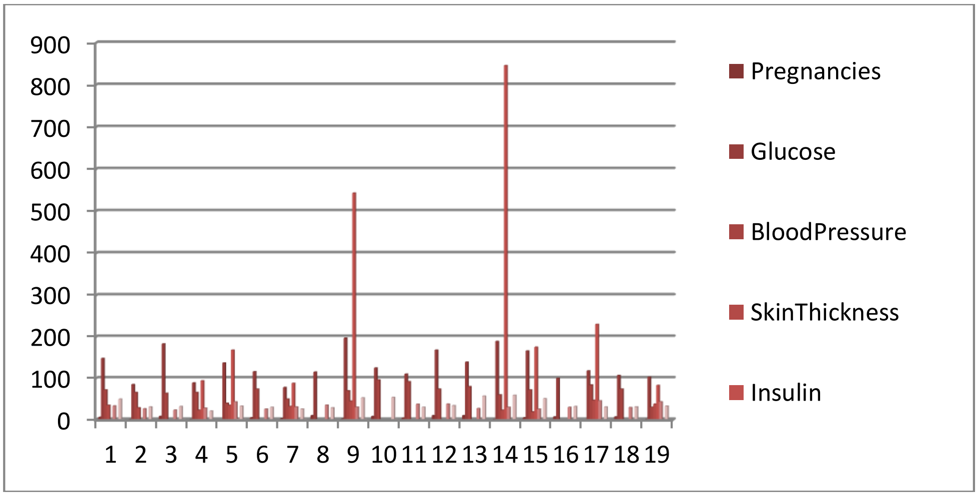
Deeraj Shetty et al. Introduced an information mining-based diabetes sickness expectation framework called Intelli-gent Diabetic Disease Prediction System, which gives an examination of diabetes illness utilizing a data set of diabetes patients. In this methodology, they propose utilizing Bayesian and KNN (K-Nearest Neighbor) calculations to a diabetes patient data set and analysing it using multiple diabetes variables to forecast diabetes disease. Muhammad Azeem Sarwar and colleagues proposed a study on diabetes prediction using machine learning algorithms in healthcare, in which they used six distinct machine learning algorithms. The performance and accuracy of the algorithms used are compared and evaluated. The study's comparison of the various machine learning techniques reveals which algorithm is most suited for diabetes prediction. Researchers are interested in diabetes prediction in order to train a programme to detect if a patient is diabetic or not by using an appropriate classifier on a dataset. The classification procedure, according to earlier research, has not significantly improved Poongodi et al [21-25].

Dataset Description

This presented dataset is at first from National Institute of Diabetes and Digestive and Kidney Diseases. The goal of the dataset is to clearly figure whether or not a patient has diabetes, considering unequivocal intelligent evaluations related with the dataset. Two or three targets were put on the choice of these cases from a more noteworthy enlightening list. Specifically, here all the patients are females something like 21 years of age of Pima Indian legacy. The datasets joins a couple of the clinical pointer parts and one objective variable, Outcome. Here, the pointer factors combine how many pregnancies the patient had, about their BMI, insulin level, age, etc

Table 1: Ist Datasets includes of numerous medical predictor variables

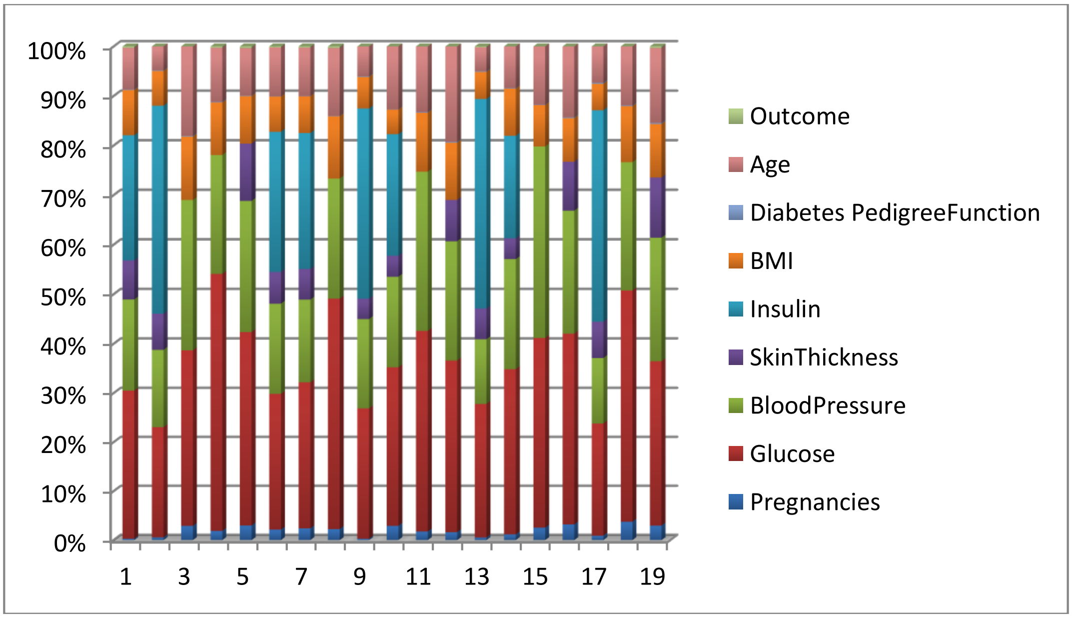
Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabetes Pedigree Function	Age	Outcome
6	148	72	35	0	33.6	0.627	50	1
1	85	66	29	0	26.6	0.351	31	0
8	183	64	0	0	23.3	0.672	32	1
1	89	66	23	94	28.1	0.167	21	0
0	137	40	35	168	43.1	2.288	33	1
5	116	74	0	0	25.6	0.201	30	0
3	78	50	32	88	31	0.248	26	1
10	115	0	0	0	35.3	0.134	29	0
2	197	70	45	543	30.5	0.158	53	1
8	125	96	0	0	0	0.232	54	1
4	110	92	0	0	37.6	0.191	30	0
10	168	74	0	0	38	0.537	34	1
10	139	80	0	0	27.1	1.441	57	0
1	189	60	23	846	30.1	0.398	59	1
5	166	72	19	175	25.8	0.587	51	1
7	100	0	0	0	30	0.484	32	1
0	118	84	47	230	45.8	0.551	31	1
7	107	74	0	0	29.6	0.254	31	1
1	103	30	38	83	43.3	0.183	33	0



Graph 1: Ist Datasets includes of numerous medical predictor variables

Table 2: IInd Datasets consists of several medical predictor variables

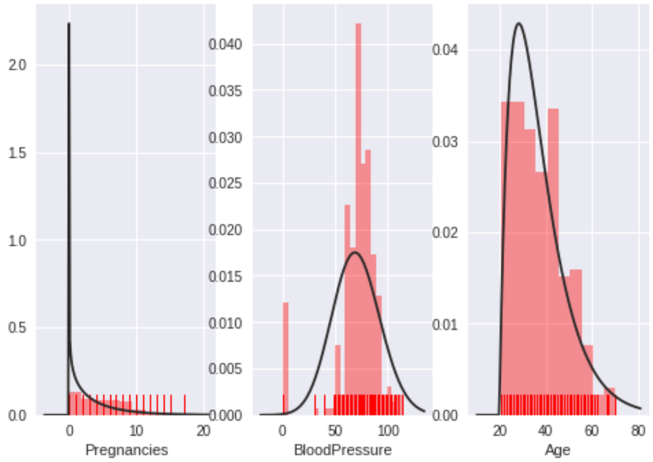
Pregnancies	Glucose	Blood Pressure	Skin Thickness	Insulin	BMI	Diabetes Pedigree Function	Age	Outcome
1	115	70	30	96	34.6	0.529	32	1
3	126	88	41	235	39.3	0.704	27	0
8	99	84	0	0	35.4	0.388	50	0
7	196	90	0	0	39.8	0.451	41	1
9	119	80	35	0	29	0.263	29	1
11	143	94	33	146	36.6	0.254	51	1
10	125	70	26	115	31.1	0.205	41	1
7	147	76	0	0	39.4	0.257	43	1
1	97	66	15	140	23.2	0.487	22	0
13	145	82	19	110	22.2	0.245	57	0
5	117	92	0	0	34.1	0.337	38	0
5	109	75	26	0	36	0.546	60	0
3	158	76	36	245	31.6	0.851	28	1
3	88	58	11	54	24.8	0.267	22	0
6	92	92	0	0	19.9	0.188	28	0
10	122	78	31	0	27.6	0.512	45	0
4	103	60	33	192	24	0.966	33	0
11	138	76	0	0	33.2	0.42	35	0
9	102	76	37	0	32.9	0.665	46	1



Graph 2: Graphical view of IInd Datasets consists of several medical predictor variables

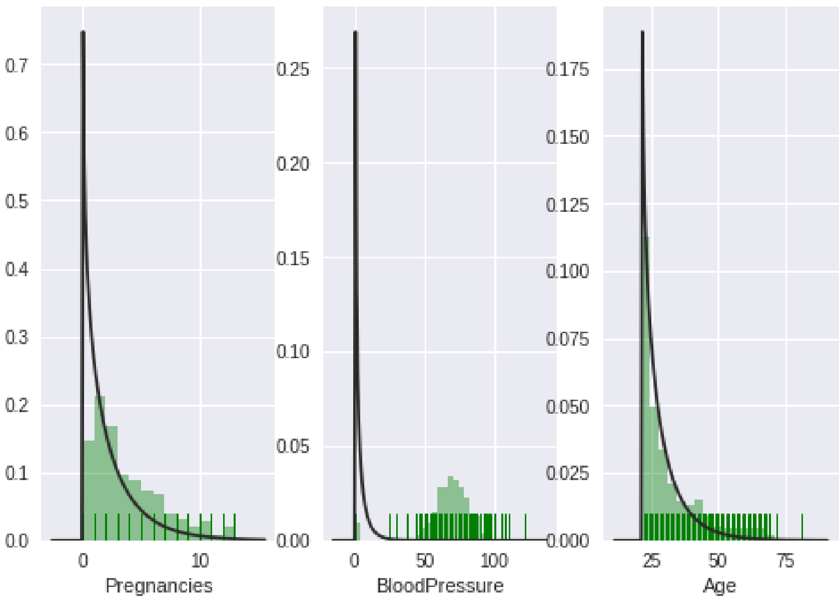
Methodology

Upon splitting the dataset into Positive and Negative examples, we analyze any visible trends in the positive and negative examples. The below are plots of variables that show trends in relationship with respect to the outcome (postive or negative). The plots show below only depicts variables with a visible relation. The **red** graphs indicate **positive examples**, while **green** graphs indicate **negative examples**.



Graph 3: Positive Analytical Examples

Negative Examples



Graph 4: Negative Analytical Examples

Correlation between variables with SPSS Entry Set

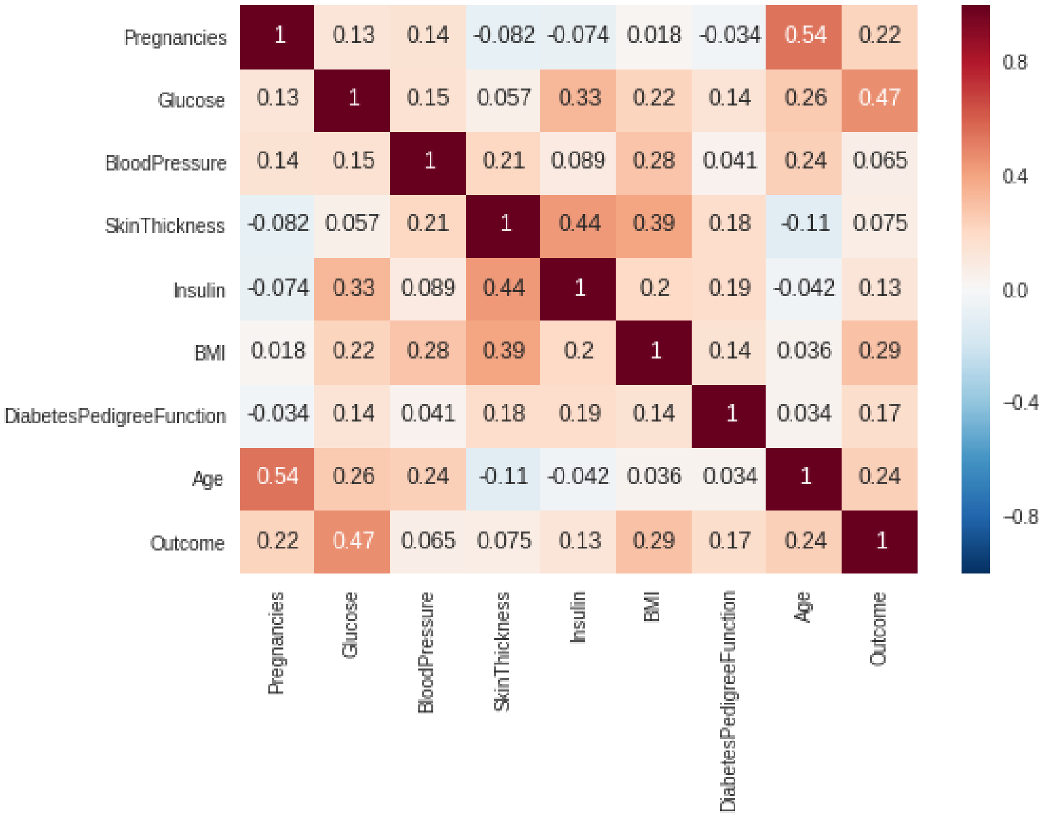


Figure 1: Confusion Matrix of Correlation between variables with SPSS

Predictive Modeling

The majority of samples in the data set are negatives with 500 examples making 65.104% of the data. If we were to simply predict negative for every value we would get an accuracy of 65.104% on this dataset. So it would be the baseline accuracy for evaluating learning algorithms.

MODEL (Artificial Neural Networks (ANN))

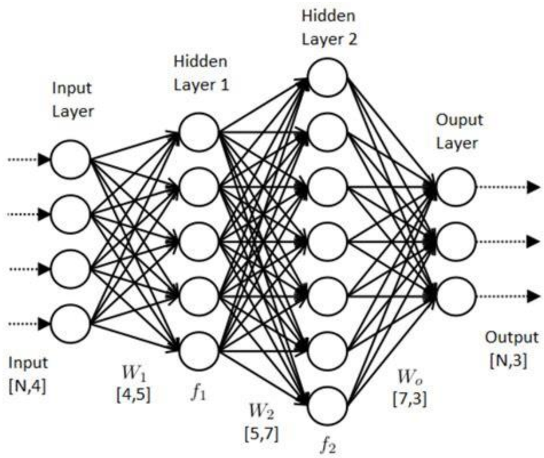


Figure 2: Model of Artificial Neural Network (Ognjanovski 2019)

Attribution Information Gain

$$Gain\ (A) = info\ (D) - info\lambda^{(D)} \ldots\ldots\ldots\ldots\ldots(1)$$

Pre-segmentation Information entropy

$$info_{\lambda} = Entrophy\ (D) = \textstyle\sum_j p\ (j|D\ ) \log p\ (J\ |d\ ) \ldots\ldots\ldots.(\ 2\ )$$

Distribution Information entrop y

$$info_{\lambda}(D) = \textstyle\sum_j^v \frac{n_1}{n} \text{info (D)} \ldots\ldots\ldots\ldots\ldots(\ 3\ )$$

The model to extract principal component factors is:

$$f_{1= T_n} X_{12} X_2 + T_{tk} X_k (i = 1, \ldots\ldots, m) \ldots\ldots\ldots.(\ 4\ )$$

$$SN = \frac{TP}{TP+FN} \ldots\ldots\ldots\ldots.(\ 5\ )$$

$$SN = \frac{TN}{TP+FN} \ldots\ldots\ldots\ldots\ldots(\ 6\ )$$

$$ACC = \frac{TP+TN}{TP+FN+\ TP+FN} \ldots\ldots\ldots\ldots.(\ 7\ )$$

$$MCC = \frac{(TP\times TN)-(\ FN\times FP)}{\sqrt{(TP+TN)-(\ FN+FP)\times(TP+FP)\times(TN+FN)}} \ldots\ldots.(\ 8\ )$$

The quantity of recognized positive examples in the positive set is addressed by obvious positive (TP). The quantity of arrangement negative examples in the negative set is alluded to as evident negative (TP). The quantity of perceived positive examples in the negative set is how much bogus up-side (FP). The quantity of perceived negative examples in the positive set is addressed by bogus negative (FN).

Classification Report

Precision	**Recall**	**F1-score**	**support**
0	0.81	0.88 0.85	254
1	0.74	0.58 0.65	132
Avg / total	0.77	0.79 0.78	385

The accuracy, review, F1, and backing scores for the model are shown in the grouping report visualizer.

Table 3: Tabular view of grouping report

precision	recall	f1-score	support
0	0.92	0.91	12500
1	0.93	0.92	12500
micro avg	0.92	0.92	25000
macro avg	0.92	0.93	25000
weighted avg	0.92	0.93	25000

There are four different ways referenced to check in the event that the forecasts are correct or then again off-base:

1. **TN/True Negative:** here the case was negative and expected negative
2. **TP/True Positive:** here the case was positive and expected positive
3. **FN/False Negative:** here the case was positive at this point expected negative
4. **FP/False Positive:** here the case was negative anyway expected positive

Still up in the air as the extent of veritable up-sides of how much real up-sides and bogus up-sides for each class.

Accuracy:

- Positive forecast exactness.

Accuracy = TP/(TP + FP)

The limit of a classifier to observe every one of specific cases is known as audit. Still up in the air as the proportion of genuine up-sides of the amount of genuine up-sides and bogus negatives for each class.

Review: The level of up-sides accurately detected.

Recall = TP/(TP+FN)

The F1 score is a weighted symphonious mean of exactness and audit, with 1.0 being the most raised moreover 0.0 being the least. F1 scores are lower than accuracy evaluations since they factor on accuracy and review. To analyze classifier models, use the weighted normal of F1 rather than worldwide exactness as a guideline.

F1 Score = 2*(Recall * Precision)/ (Recall + Precision)

Results

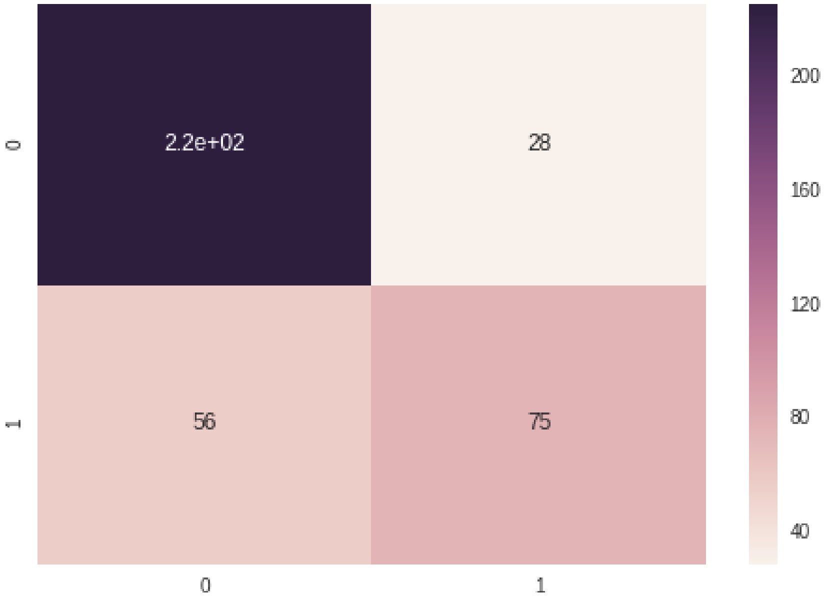


Figure 3: Accuracy Parameter Output

Accuracy: 0.776097105509

Accuracy = 77.9%

Conclusion

Early detection of diabetes can help patients improve their quality of life and extend their life expectancy. Different diabetes detection methods have been developed using supervised algorithms. Diabetes mellitus is a sickness that can prompt an assortment of issues. It's significant seeing the way that AI can be utilized to precisely figure and analyze this condition. According to the findings of all of the aforementioned studies, we discovered that the exactness of PCA is poor, and that the consequences of utilizing all elements and mRMR are predominant. The outcome that basically utilized fasting glucose performed better, prominently in the Luzhou dataset. It truly plans that while fasting the glucose is the guideline list is to predict, we can't get the best results just by using fasting glucose, thus we'll need more indices if we want to forecast accurately. Furthermore, while looking at the consequences of three orders, we can see that there isn't a very remarkable distinction between irregular woods, choice tree, and neural organization, albeit arbitrary woodlands are plainly better than different classifiers sometimes. The best exhibition for the Luzhou dataset is 0.8085, while the best show for the Pima Indians is 0.7721,showing that AI can be utilized to anticipate diabetes, however selecting appropriate features, classifiers, and data mining methods is crucial. Because we can't identify the kind of diabetes based on the data, we'll try to forecast it in the future and look into the proportions of each signal to see if we can enhance the accuracy of diabetes prediction.

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