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Bionic Health-Care Innovation Using Artificial And Human Intelligence

[1]Sheela D. V., [2]Abhay Chaturvedi, [3]Prajakta Naregalkar, [4]Dr. M. Chiranjivi, [5]Chetan More, [6]Namita K. Shinde, [7]*Dr. Anurag Shrivastava

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Abstract: According to the findings of a pilot investigation, women who have type 2 diabetes (T2DM) have an increased chance of developing breast cancer. In this study, we compared the accuracy of three different models for determining the likelihood of developing breast cancer in type 2 diabetics who had different characteristics at the outset. The information was included into a model with the goal of determining whether or not a patient with type 2 diabetes also had a higher risk of acquiring breast cancer. In addition, we conducted research to identify potential breast cancer risk factors in order to incorporate their influence into our study and take appropriate action. Researchers have turned to a method known as synthetic minority oversampling in order to gather more information from samples of communities who are underrepresented in their studies. The ratio of training data to test data was close to 39 to 1 for each question in the survey. The effectiveness of the Logistic Regression (LR), Artificial Neural Network (ANN), and Random Forest (RF) models were evaluated using metrics such as recall, accuracy, F1 score, and area under the receiver operating characteristic curve (AUC), respectively. The area under the curve (AUC) for each of the three models was comparable (0.83 for LR, 0.865 for ANN, and 0.959 for RF). The RF model has the greatest AUC out of the three that were taken into consideration. When it came to forecasting whether or not T2DM patients will get breast cancer, the RF model performed the best out of the LR, ANN, and RF models.

***Keywords**: Artificial intelligence, wearable devices, healthcare, point-of-care sensors, and smart sensors are some of the areas of focus in this industry.*

1. Introduction

Diabetes, which is one of the health issues that is rising at a rapid rate, requires that one's blood glucose levels be checked on a consistent, automated basis. A measurement of the patient's blood glucose level is one of the most significant diagnostic tests for individuals who have hypoglycemia and hyperglycemia. Around the world, there are more than 425 million people living with diabetes, and the condition accounts for 12 percent of all healthcare spending. People who have diabetes are at an increased risk of developing diabetic retinopathy (DR), which is the major cause of vision loss and blindness in this population [1]. Studies on illness prevalence and risk factors called epidemiological studies demonstrate that one-third of diabetics have diabetic maculae oedema. This condition presents as minute protrusions from the artery walls and leaks blood into the retina. Epidemiological studies are used to study disease prevalence and risk factors. Diabetics have a risk of developing DR at a rate of one in three. Monitoring blood glucose levels regularly and accurately is essential for reducing the risk of both acute and long-term clinical complications associated with diabetes. It is of the utmost need to build a generation of glucose monitors for patients at a price that is affordable and does not require them to repeatedly prick their fingertips to check their glucose level, as this is the method that has historically been utilised. Methods for measuring plasma glucose in patients that are electrochemically based are now available for purchase in commercial settings [2].

Glucometers are becoming more and more commonplace in the treatment and management of type 2 diabetes, in spite of certain reservations regarding the accuracy and precision of such devices. As contrast to a point-of-use glucose metre, which can only provide a snapshot of glucose trends, a continuous carbohydrate device gives the patient and the carer real-time information on glucose

1Assistant Professor, School of Computer Science and Application, REVA University,
Bangalore
sheela.dv@reva.edu.in
2Associate Professor, Department of Electronics and Communication Engineering, GLA University, Mathura, Uttar Pradesh, 281406
abhaychat@gmail.com
3Assistant professor, Bharati Vidyapeeth (Deemed to be University) College of Engineering, Pune
pdkulkarni@bvucoep.edu.in
4Associate Professor, Department of EEE, Hyderabad Institute of Technology and Management, Telangana -501401
chiranjivimadduluri@gmail.com
5Assistant Professor, Department of E&TC, Bharati Vidyapeeth (Deemed to be University) College of Engineering, Pune
csmore@bvucoep.edu.in
6Assistant Professor, Department of E&TC, Bharati Vidyapeeth (Deemed to be University) College of Engineering, Pune
namitak.shinde@gmail.com
[7]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai,
Tamilnadu, India
**anuragshri76@gmail.com*

tiers. This allows for more accurate management of the patient's condition. The complexity of blood dynamics is one of the most significant obstacles in the way of accurate and prompt glucose stage prediction. Because of the complex nature of blood dynamics, it can be difficult to make accurate and timely predictions on a person's blood glucose level. Because of their capacity to foresee diabetes trends and identify people who are at risk for getting the illness, algorithms that are based on artificial intelligence (AI) and machine learning (ML) play an essential role in the treatment of diabetes.

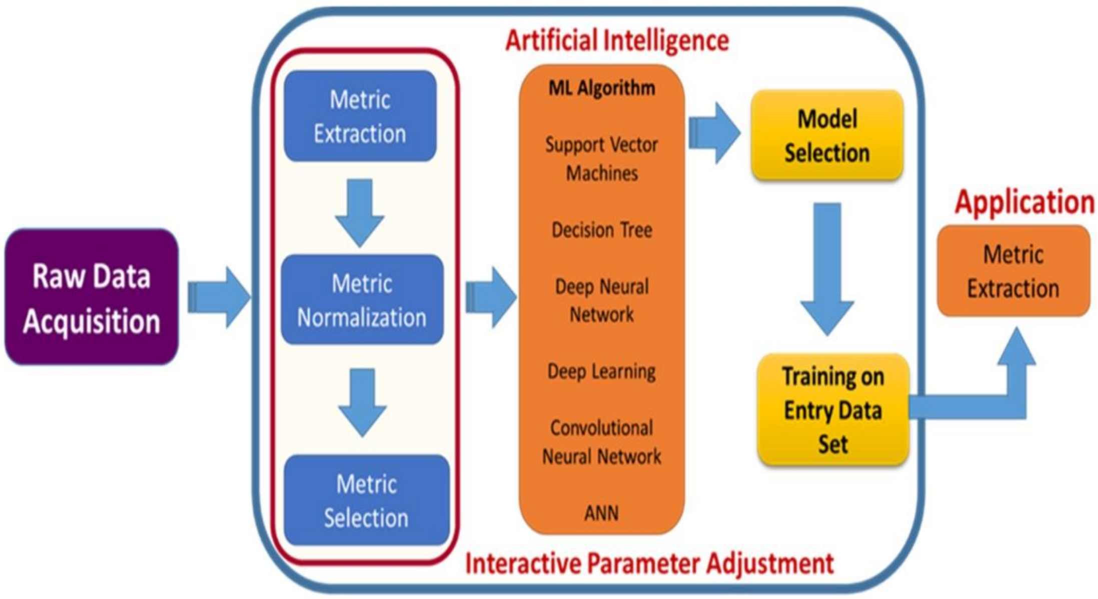

Fig 1. Conventional AI based healthcare system []

products like as glucose monitoring devices are examples of products that employ AI and ML to increase the accuracy of scientific research. developed a gadget that uses artificial intelligence to determine the amount of glucose present in the blood [4]. The criteria for entrance include age, pregnant status, body mass index, glucose levels, and insulin levels. The ruleset is based on these five entry parameters. Several machine learning methods, including random forests, neural networks, decision trees, and k-nearest neighbour (KNN) algorithms with hidden layers, were utilised in the analysis of the dataset. More than seventy percent of the glucose readings provided by each model could be relied upon as accurate. hybrid technology Hamdi et al. [5] exploited compartmental techniques to measure glucose levels. A CGM system was used to monitor glucose levels while following a rule set that was generated by an ANN. The monitoring device for glucose levels consists of a subcutaneously implanted sensor and a wireless transmitter. The transmitter transmits data wirelessly. The glucose levels of the patient are checked by the device once every 15 minutes. Data from 12 patients was obtained for both the training and validation phases, which proved to be an excellent way for evaluating the device's overall performance in clinical analysis. This data was acquired from both the training phase and the validation phase. The input layer, the hidden layer, and the output layer make up its structure [6].

Finding patterns and correlations in non-linear statistical data may be done using the SML techniques, which can be utilised to analyse the data. It is imperative that non-linearity be decreased in glucose sensors before they may be utilised in clinical settings. The data contributed by eleven different authors was gathered and used in the training of the algorithm. In the current generation of continuous glucose monitors (CGM), glucose levels are measured using interstitial fluid (ISF). However, it has been known for a very long time that the glucose levels in the two compartments rise at distinct periods, often anywhere from five to twenty-five minutes apart [7].

As a result of this latency, computerised insulin injections are not something that is suggested for CGMs. Unfortunately, the CGM frequently fails to identify episodes of low blood sugar. Artificial pancreas devices that include CGM are a possibility for this population given that it is anticipated that blood sugar levels would begin to rise a half an hour sooner [8]. Continuous glucose monitoring using the invasive and time-consuming finger-prick method may one day be replaced by the less invasive and more convenient non-invasive glucose sensing method. For the purpose of monitoring glucose levels in the blood, ML-based optical sensors have been presented [9]. These sensors make use of light sources that emit light at varied wavelengths. In addition to the more than twenty-one non-standard light sources of varied wavelengths that were employed, there were also more than five separate methodologies used to analyse the system.

This article demonstrates how artificial intelligence (AI) is conceived of as a digital innovation by utilising examples from the healthcare sector and classic works on management. The implications and uses of AI will be discussed in Part 4, which may be found here. In the next paragraph, we will address the potential impact that artificial intelligence (AI) may have on future forms of healthcare delivery. The intended work comes to a close with its fifth and final section.

2. Literature Survey

In literature, ability applications of synthetic intelligence are properly documented; some are based totally on reality, while others are in simple terms hypothetical. Research have to this point tested that AI is capable of doing a little jobs higher than human docs in a selection of scientific specialties, together with dermatology, cardiology, and radiology. AI structures could be capable of understand functions and patterns that are invisible to human beings thanks to deep studying skills [10]. This changed into verified via the Deep affected person attempt, which noticed a research crew at Mount Sinai medical institution in ny train a pc the use of the electronic health information of 700,000 patients before the usage of the software program to predict illness in a second sample of seventy six, human beings. In step with their evaluation, the effects "drastically exceeded" the ones attained using the exchange function studying techniques and raw health record information. It is challenging to understand how those kinds of structures get the consequences they do, although, because the software program teaches itself styles. Extra tasks of a comparable nature have generated stunning media testimonies about AI replacing physicians [11].

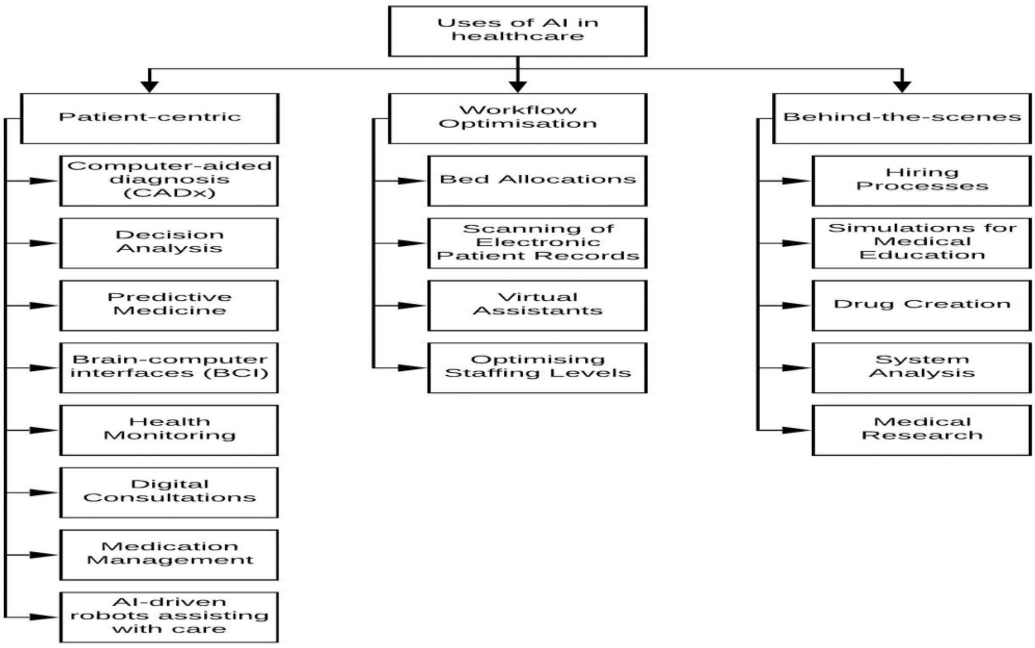

Fig 2. AI based healthcare methodologies [12]

However, as proven in figure 2, there are numerous programs of AI that sufferers may not be able to see proper away. those packages name for "deductive" AI structures, which could have a look at statistics to become aware of patterns which might be not possible for people to pick out up on. though their utilization in scientific practice is restrained, it's far essential to highlight that "genera tive" AI systems also are growing. those structures have the ability to produce artificial statistics after being skilled on an existing dataset [13]. They can, however, indirectly improve patient outcomes, for instance by giving doctors access to educational materials. As AI becomes more complex, research steadily tries to connect many technologies to create synergies, such as with robots, the internet of things, and patient document manipulation systems. The science of artificial intelligence (AI) has the potential to be incredibly creative, and new applications will undoubtedly emerge. Some people have even expressed concern that AI may be used to continually improve itself, raising the possibility that its capability may someday surpass that of human programmers [14].

This might start a recursive cycle of self-improvement wherein improvements additionally make the method of improvement higher. This capability is called a "singularity" or "intelligence explosion" by means of specialists within the situation. it's miles important to observe a critique of this prediction's application in practice at this point. whilst applied AI has thus far shown to be fantastically powerful at completing narrowly focused responsibilities, advancements closer to artificial general intelligence (AGI) were less innovative. One can also argue that the increasing amount of "singularity" discussion is untimely and deflects attention from greater pressing social and ethical problems brought on with the aid of present day gadget ingenuity [15].

AI diagnostic structures employ machine learning to find patterns that could be impractical to implement. These algorithms require large, expert datasets in order to produce reliable results. There is a genuine possibility that AI systems might generate biassed decisions as a result of biassed algorithms or unrepresentative datasets that were used to analyse the ones datasets. Before AI systems can be fully implemented, it is crucial to make sure that the educational datasets are appropriate for the population that the algorithms will eventually serve. For example, it has been noted that the majority of dermatological algorithms are developed on Caucasian or Asian patients, but that unless the algorithms have been correctly trained, they would produce inaccurate results when applied to patients of diverse races [16].15 Human docs utilize a diffusion of facts about specific patients, inclusive of scientific statistics, prescription histories, and actual-time data, to help them make choices. A lot of the statistics, in particular the symptoms of the sufferers, is tough to codify and consequently difficult to investigate. Given the variation within the format and style of medical facts amongst healthcare systems, it will be especially challenging to solve the issue of data homogenization.

3. Proposed Methodology

3.1. Data Source

Since 1995, the government of Taiwan has been in charge of running a national health insurance programme (NHI) that presently covers 90 percent of the population. For the purpose of this study, data from the Longitudinal Cohort of Diabetes people from the NHI were utilised. This cohort consists of 1,700,000 people who recently received a diagnosis of type 2 diabetes and were assigned the ICD-9-CM codes 250x0 and 250x2 [17]. Since 1995, the government of Taiwan has been in charge of running a national health insurance programme (NHI) that presently covers 90 percent of the population. For the purpose of this study, data from the Longitudinal Cohort of Diabetes people from the NHI were utilised. This cohort consists of 1,700,000 people who recently received a diagnosis of type 2 diabetes and were assigned the ICD-9-CM codes 250x0 and 250x2 [17].

3.2. Data Availability Statement

The study made use of the statistics provided by the Ministry of Health and Welfare in Taiwan. After properly submitting an application for the datasets and being granted a MOHW authorization [18], researchers are granted access to the datasets.

1.3. Sampled Participants

We offered protection to female patients who had data that showed an analysis of type 2 diabetes twice or more in the span of a single year between the years 2000 and 2012. The day on which the initial diagnosis of type 2 diabetes was made became the index date. Patients who were female and less than twenty years old who had information that suggested they could have breast cancer (ICD-9-CM code 174) were not included in the study prior to this date. Employment, amount of urbanisation, and age were the three most important aspects of the legacy. Chronic kidney disease (CKD), hyperlipidemia, high blood pressure, cerebrovascular coincidence, adiposity, noncancerous circumstance, congestive coronary heart failure, chronic obstructive pulmonary disease, allergies, coronary artery illnesses, smoking, and alcohol-related infection are some of the comorbid conditions that are taken into account at baseline. The adapted Insulin complication Severity Index (aDCSI) took into account seven different types of diabetic complications: cardiovascular issues, cerebrovascular headaches, peripheral artery disease, metabolic complications, nephropathy, retinopathy, and neuropathy. These seven different types of complications were broken down into seven different categories. The use of certain medications, such as aspirin, hormone, insulin, spironolactone, pastime that takes place (TZD), and metformin, was investigated in order to ascertain whether or not a link exists between the consumption of those medications and the development of breast cancer [19].

3.4. Algorithm Training and Evaluation

The ANN model consists of three layers: an input layer with 37 dimensions, a hidden layer with 20 dimensions, and an output layer with a few dimensions. After every pair of hidden layers that the model had, an application of the Scaled Exponential Linear Unit as well as the Softmax activation function was carried out. The ultimate version was perfected by being trained in Adam with a move-entropy loss, which allowed for optimisation. Following the application of the input and hidden layers came a dropout regularisation with percentages of 20% and 50%. For the LR model, we utilised the one-vs.-relaxation approach for the loss function, the L2 loss for regularisation, and the liblinear solver for optimisation. The RF model has a regularisation power of 1, and it was trained for a total of 100 iterations using 20 selection trees and a tree intensity that was cranked up to a maximum of 10. It was determined that the quality of the split may be measured by the genie's level of purity. There are at least two samples associated with each fissure, and at least one pattern may be found associated with each leaf. When developing our LR and RF models, we made use of scikit-research (version 0.20.1) and Tensorflow (version 1.12.0), respectively [20]. The ANN redesign made use of Python in some capacity.

Model selection and fine-tuning started strongly relying on the precision of the k-fold bridge, which was set to 10. After all other aspects of the evaluation and training had been completed, the test set provided the most accurate assessment of the model's overall performance. This component of the model was not always incorporated into the model. The resultant models were evaluated using several different metrics, including area under the ROC curve (AUC), F1 (relative indication between precision and don't forget), retention (sensitivity), and precision (excellent prediction cost). After ROC curves were generated in line with prediction probabilities, the AUCs were analysed with the DeLong test [21], which was then used to evaluate the results.

1.4. Statistical Analyses

The student's t-test and the Chi-square test (for underlying illnesses, weight problems headaches, and medicines) were used to investigate the sociodemographic proportions, underlying diseases, and differences between patients who had and did not have breast cancer in those regions (for proportions).

4. Results and Discussion

There is some evidence to suggest that diabetes type 2 is linked to some cancers [4-10]. Cancer cells have a greater requirement for glucose for the creation of energy than healthy cells do, which is the primary reason for the "out-of-control" proliferation of cancer cells. When seen from a more holistic standpoint, the vast majority of cancer cell clusters may be compared to parasites that battle with the host for limited but essential resources such as glucose [9]. According to the findings of a number of research [11–17], women who have type 2 diabetes have an increased risk of getting breast cancer in comparison to women in the general population. In spite of the fact that type 2 diabetes and cancer share a number of risk factors, such as obesity, age, a diet rich in fat, and a lack of physical activity [7], there are a number of scientifically viable hypotheses for why type 2 diabetes could be a marker of breast cancer. In the first place, an increased insulin level owing to insulin resistance may result in a genetic change in breast tissue as well as an increase in cell development. In addition to this, it is common for breast cancer cells to have an overabundance of insulin receptors. Second, having type 2 diabetes, which is associated with continuous low-grade inflammation, can make breast cancer more severe. Third, there is a possibility that the link between type 2 diabetes and breast cancer will change based on the treatment that is used for the illness. Metformin and other medications that improve insulin sensitivity may lower the risk of breast cancer, whereas treatments that raise insulin levels may raise the risk of other cancers. We included drugs that have the ability to change this connection in order to clear up any ambiguity in the findings.

Table 1. Comparison of different models for conventional dataset

Model	F_1	Precision	Recall	AUROC
RF [22]	0.799	0.792	0.791	0.866
LR [23]	0.774	0.766	0.764	0.835
ANN [24]	0.893	0.893	0.893	0.969

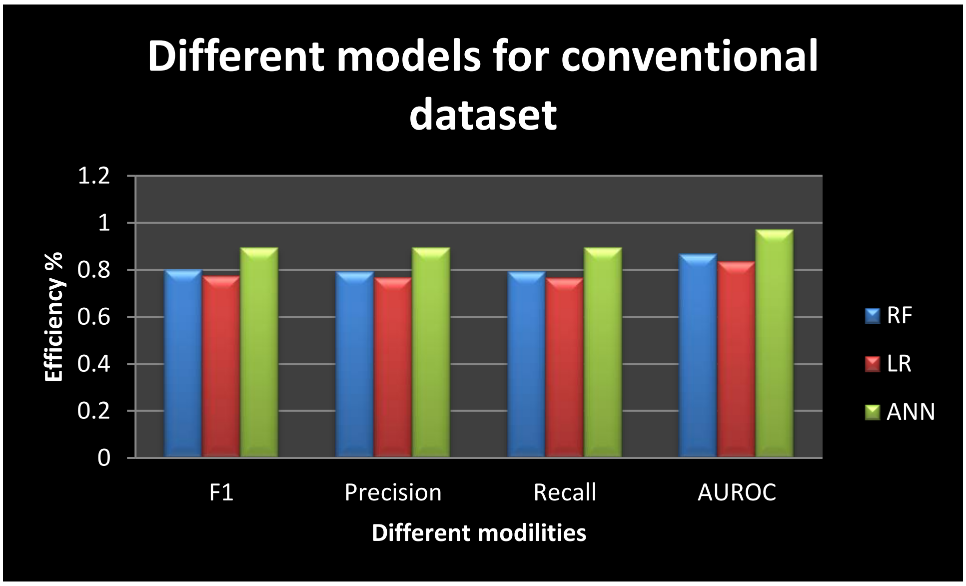

Fig 3. Comparison of different models for conventional dataset

Table 2. Comparison of different models for conventional dataset with Train

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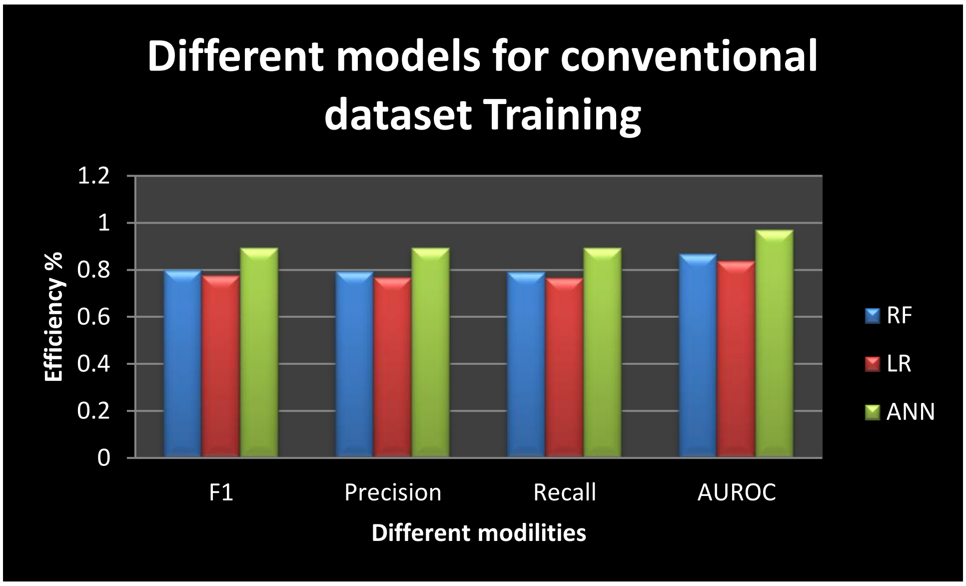

Fig 4. Comparison of different models for conventional dataset with Train

Table 3. Comparison of different models for conventional dataset with Test

Model	F_1	Precision	Recall	AUROC
RF [22]	0.793	0.790	0.790	0.862
LR [23]	0.771	0.763	0.762	0.833
ANN [24]	0.890	0.890	0.890	0.964

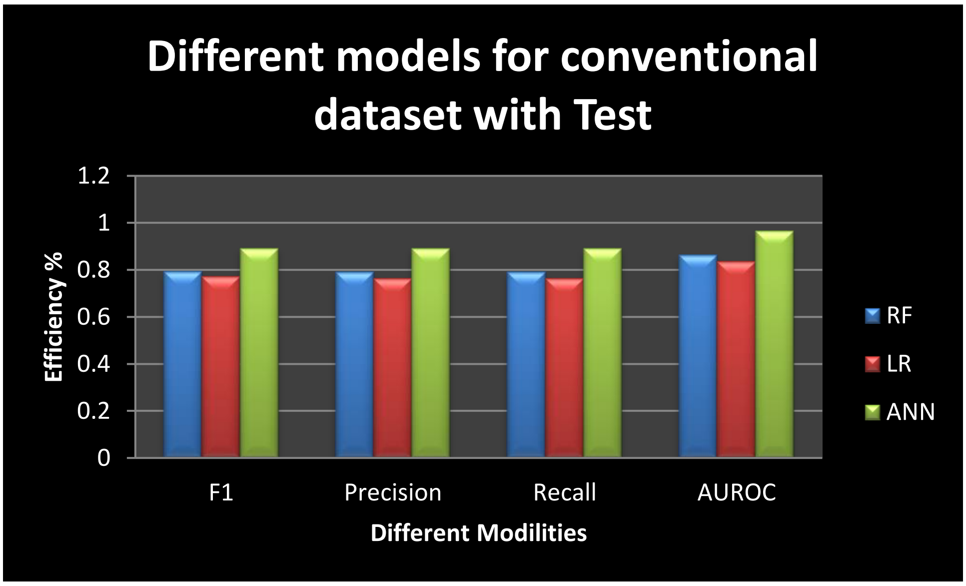

Fig 5. Comparison of different models for conventional dataset with Test

5. Conclusion

It is possible that type 2 diabetes, on its own, raises the risk of breast cancer in Taiwanese women, although this is contingent on the features of the disease. Additionally, the RF model offers the best prediction accuracy when it comes to breast cancer. Our findings imply that individuals with T2DM who are at an early stage should be included in breast cancer monitoring programmes. This is because the average age at which breast cancer is diagnosed in Taiwan is rather young.

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