# A Multi-Disease Prediction System for Diabetic Complications Using Machine Learning and Deep Learning

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***Abstract*—** Diabetes mellitus is a problem that affects many parts of the body and gets worse over time . near of the ways we try to predict what will happen to people with Diabetes mellitus only look at one thing at a time . This study is trying to do something . It is trying to make a system that can predict all the complications of Diabetes mellitus . The system uses things like blood sugar levels , heart health, kidney health and how extendable someone has had Diabetes mellitus to make predictions. It uses these things to predict if someone will get nerve damage kidney damage or heart problems. The system uses a kind of computer program called Random Forest models to make these predictions. It also uses a kind of computer program called a convolutional neuronic network to look at pictures of the eyes and predict if someone will obtain eye damage from Diabetes mellitus. All of these predictions are then combined into one score that shows the risk of complications from Diabetes mellitus. This score can help doctors understand what might happen to people, with Diabetes mellitus. The system is deployed as a web based application, enabling real time, extensive risk assessment to support proactive clinical decision making.

**Keywords—** Diabetes mellitus, ill complications, multi-disease prediction, machine learning, intense learning, Random Forest, convolutional neuronic network, risk assessment, non-subjective decision support, healthcare analytics.

## I. INTRODUCTION

Diabetes mellitus is a problem that people have to deal with for a long-dated time. It is a condition where the body has much sugar in the blood. This happens because the body does not make sufficient insulin or the insulin does not work properly .Diabetes mellitus has become a conspicuous issue all about the world . further and more people are getting diabetes mellitus. This is a concern for people who take care of open health .The problem with diabetes mellitus is not just that it messes up the way the body uses sugar . Diabetes mellitus can also cause a lot of problems over time . These problems can hurt parts of the body and make people die sooner. They can also make life not as enjoyable.

Some common problems that people, with diabetes mellitus get include nerve damage, kidney damage, eye damage and heart disease. Diabetes mellitus can cause all these problems and more. These health problems usually start without us even noticing. We only find out about them when it is too late and the damage is done. The conditions often develop silently. Then become clinically evident only after the irreversible damage has occurred to the conditions.

Finding out about complications early on is really important. If doctors catch these problems enough they can help slow down the disease and stop some really bad things from happening like people going blind having kidney problems losing a limb or having heart problems. Doctors can also save money on healthcare costs.

In the world when doctors check patients for these complications it is often done in a way that is not very organized. Patients have to go to doctors and have separate tests at different times. Each test is looking for something. This way of doing things can make it take longer to figure out what is wrong, with the patient. It also does not take into account that diabetic complications are all connected and can affect each other. Diabetic complications often happen at the time and can make each other worse.

Machine learning is really good at helping us figure out who is going to get sick and how bad it is going to be. Machine learning models can look at a lot of information from hospitals and doctors to find patterns that're hard to see with old ways of


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doing statistics. Deep learning is especially good at looking at pictures of people's bodies to figure out what is wrong. For example, it can look at pictures of the back of people's eyes. Tell if they have diabetic retinopathy. Even with all these good things most of the research on machine learning and diabetes is only looking at one problem at a time like just diabetic retinopathy and not all the problems that people, with diabetes might have. Machine learning and deep learning and diabetes are all. We should be looking at all of them together. These models can be really good at tasks and they get the right answer most of the time.. They are not very helpful when doctors need to make big decisions about a patients care. The models just do not know enough about all the things that can be wrong with someone. This is a problem because doctors need to consider a lot of things when they are trying to figure out what is wrong with someone and how to make them better. These models are just not good enough, for that. They are limited to a few things and that is it. Doctors need something that can help them with everything, not one or two things.

A big problem with systems that predict one disease is that they do not show the whole picture of a patients health. Diabetes affects the body and problems with it usually do not happen on their own. For instance when people with Diabetes have blood sugar control and have had the disease for a long time they are more likely to get nerve damage, kidney damage and heart disease all at the same time. If we ignore the things that increase the risk of getting these problems we end up with models that do the thing over and over waste time and money on screening and do not get a complete idea of the risks[11]. What we need is a system that can look at all the problems that can happen with Diabetes like nerve damage and kidney damage and heart disease and use both the information from the patients medical history and pictures, from medical imaging to do this.

This study is trying to fill a gap by coming up with a system that can predict problems that people with diabetes might have. The system uses machine learning and deep learning to make predictions. It looks at things like how old someone's if they are a man or a woman their blood sugar levels, blood pressure, cholesterol levels, kidney function, body mass index and how long they have had diabetes. The system uses this information to predict if someone is at risk of getting nerve damage, kidney disease or heart disease because of their diabetes. The system uses something called Random Forest classifiers to make these predictions.

These models are really good, at working with data because they are strong easy to understand and can look at how different things are related to each other[7]. Diabetes is a part of this system and it is used to predict diabetic neuropathy diabetic nephropathy and cardiovascular disease risk. At the time a special kind of computer program called a deep learning-based convolutional neural network is used to find diabetic retinopathy in pictures of the back of the eye, which is really good at recognizing patterns that we can see. The retinopathy detection is cooked by the intense learning based convolutional neuronic network, from retinal fundus images . The proposed system does something important. It takes all the predictions about diseases and puts them together into one score. This score shows the risk of complications. Doctors like this because they get one number that tells them about the gross risk. They do not have to look at a lot of predictions. This is like what doctors really do when they are treating patients. They think about the patient , not just one problem at a time. The disease predictions are used to make the complication risk score. This prospective complication risk score is useful , for doctors.

To enhance hard nosed applicability , the proposed framework is implemented as an synergistic web based application . The system allows clinicians to input enduring data, upload retinal images , and receive real time predictions along with clear visualizations of disease specific risks and overall complication likelihood . This design emphasizes usability and supports early frustrating decision making in both hospital and remote care settings.

## II LITERATURE REVIEW

The number of people with diabetes mellitus is going up fast entirely over the world .This has made a lot of people do research on how to predict when people, with diabetes will have health problems. They want to do this before it's too late . normally doctors look at test results .Use their own experience to make decisions . This is not always good enough because it does not take into account how entirely the unusual risk factors work together. So now people are using machine learning and intense learning to try and predict what will happen to people with diabetes . They think that diabetes care will be better if they use these methods. Diabetes mellitus is a problem and machine learningand intense learning can help with it.

People did some studies to figure out if they could predict when someone with diabetes would have complications. The people who wrote [1] old some math to try and predict when someone would get nephropathy. They old things like HbA1c and serum creatinine to make their predictions. Their model was pretty kind at first. It did not work very well when they tried to utilize it with unusual types of patients. This showed that simple models do not always work. The people who did the work in [2] old something called support vector machines to try and predict when someone would get ill neuropathy. They were able to predict it a insignificant but they had to do a lot of additional work to get the model to work properly . ill complications like nephropathy and ill neuropathy are what the people in these studies were trying to predict. They used diabetes models to do this. Diabetes models are important, for predicting complications.

Random Forest classifiers are really good at handling a lot of medical information. They are very strong. Can deal with many details at the same time. For example a system that uses Random Forest was made to predict the risk of heart disease in people with diabetes. This system was better than the ways of predicting disease. It only looked at heart disease and not other health problems that can happen at the same time. Random Forest classifiers are often used to study one disease at a time

which's a problem because many people have more, than one health issue. This is a limitation of studies that use Random Forest classifiers to look at medical problems.

Diabetic retinopathy is something that people have looked at a lot using deep learning approaches[8]. These approaches use something called neural networks. These neural networks are really good at finding retinopathy in pictures of the back of the eye. They are almost as good as doctors at doing this. Some people wrote a paper where they made a model using neural networks. They trained this model using a lot of pictures from datasets. This model was very good at telling how severe the diabetic retinopathy was. Even though this is a result these systems that look at pictures do not use information from the patients medical history. This means they cannot give a picture of how, at risk the patient is. Diabetic retinopathy is a problem and these systems need to be able to use all the information they can get to help patients.

Machine learning and deep learning are being combined in some ways. For example in [5] they looked at data and retinal images together to see how diabetic retinopathy would progress. This method was better at making predictions. It only worked for one specific problem and did not work for other parts of the body. The problem with most of these combined systems is that they do not give an answer that doctors can understand and use to make decisions. Diabetic retinopathy is still a focus but machine learning and deep learning can be used for more, than just that. Machine learning and deep learning need to be used in a way that gives doctors the information they need to make decisions. More recent research has explored multi-disease prediction frameworks. The study in [6] proposed a multi-label classification model to predict multiple chronic diseases, including diabetes-related conditions. However, the model treated complications as independent labels and did not incorporate disease-specific modeling strategies or risk aggregation mechanisms. Additionally, limited attention was given to deployment and real-time clinical usability.

| Ref. No. | Predicted Complication(s) | Methodology Used | Data Type | Key Limitation |
|---|---|---|---|---|
| [1] | Diabetic Nephropathy | Logistic Regression, Decision Tree | Clinical Data | Limited generalization |
| [2] | Diabetic Neuropathy | Support Vector Machine | Clinical Data | Extensive feature tuning |
| [3] | Cardiovascular Risk | Random Forest | Clinical Data | Single complication focus |
| [4] | Diabetic Retinopathy | CNN | Retinal Images | No clinical data integration |
| [5] | Diabetic Retinopathy | Hybrid ML–DL | Clinical + Image Data | Single disease scope |
| [6] | Multiple Chronic Diseases | Multi-label Classification | Clinical Data | No unified risk assessment |

Table 1: Literature Review for the diabetic prediction.

## III. PROPOSED SYSTEM

The modern system is a way to predict if people will obtain significantly sick from diabetes . It looks at a lot of things like what's going on in the body and what might happen in the future . The independent goal of the system is to give doctors an idea of what problems a person, with diabetes might have so they can help them. The system uses computers to look at lots of information like what the doctors see and what the tests show. It puts all of this together in one place so the doctors can see what is going on and what might happen next . The system is made up of parts including looking at enduring information analyzing pictures of the body figuring.

The system has a part that looks at data in a structured way . It collects information about patients, such as their age , gender , HbA1c fasting blood glucose , blood pressure, heart rate , body mass index, cholesterol levels, serum creatinine and how long they have had diabetes . This information is collected through a user interface. The system uses these parameters because they are pivotal for understanding complications related to diabetes.

After the system gets this information it does some work to make sure it is usable like making sure all the numbers are, on the scale and filling in any missing information. Then the system uses this data in three Random Forest classifiers. Each model is trained to figure out how likely someone is to get a problem: diabetic neuropathy diabetic nephropathy and the risk of getting cardiovascular disease. We picked Random Forest because it is really good at handling lots of kinds of medical information it does not get confused by too much data and it can find relationships, between things that are not always straightforward.

The second part of this thing is about finding retinopathy using deep learning. We look at pictures of the back of the eye. Use a special kind of computer program to check for problems. This program is trained using a lot of pictures that're available, to anyone. It learns to find things that're wrong with the eye, like microaneurysms, hemorrhages and exudates. We do some things to the pictures first like make them the right size make them clearer and get rid of stuff we do not need. This helps the computer program work better and give us the answers every time. The computer program then tells us how promising it is that someone has retinopathy. ill retinopathy is what we are trying to find. The computer program gives us a score that says if someone has retinopathy or not.

The proposed system has an pivotal part called the risk aggregation module. It takes the results from all the disease models and puts them together to calculate a score that shows the gross risk of prospective complications. This score shows how unsatisfactory the complications, from diabetes are and it gives doctors a number that they can understand . The system uses a way of combining the results that takes into account how good each complication is and how fast it is getting worse. This separate score helps doctors make decisions about which patients need to be treated right aside or watched further closely . The risk aggregation module is a part of the proposed system and it helps with the risk score . The risk score is what doctors use to see what is going on with the patients who have diabetes.

To ensure hard nosed usability , the smooth framework is implemented as an synergistic web based application . The system allows healthcare professionals to input enduring data , upload retinal images, and receive real time predictions . Results are presented through natural visualizations , including singular risk probabilities and the gross complication score. This deployment supports speedy screening , distant monitoring , and integration into routine non subjective workflows.

## IV. System Architecture and Working

The modern system is a way to predict if people will obtain significantly sick from diabetes. It looks at a lot of things like what's going on in the body and what might happen in the future. The independent goal of the system is to give doctors an idea of what problems a person, with diabetes might have so they can help them. The system uses computers to look at lots of information like what the doctors see and what the tests show . It puts all of this together in one place so the doctors can see what is going on and what might happen next. The system is made up of parts including looking at enduring information analyzing pictures of the body figuring out what the risks are and showing all of this information in veridical time.

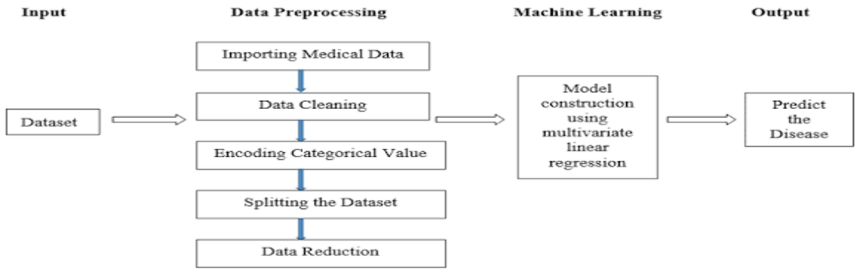


**Fig 1:** Architecture and working

The architecture starts with the data input layer . This is where users put in their information. The data input layer takes two kinds of information: non subjective data that is orderly and retinal fundus images. The non subjective data has things like the users details , essential signs , biochemical parameters and their history with diabetes. The system checks these things to make sure they are hearty and right before it does anything with them . The retinal fundus images have to be , in a format. The system checks the images to make sure they are kind quality. This is pivotal because rotten images can give results . The data input layer is an pivotal part of the architecture . It sets the stage for the rest of the process. The nonsubjective data and retinal fundus images are the foundation of the architecture.

The preprocessing layer gets the input data prompt for the model to use . The nonsubjective data needs to be normalized. Encoded so it can handle the unusual scales of measurement and categories.If there are missing values they are filled in using methods that make sense from a statistics point of view so the data stays good. For pictures the preprocessing steps are making them all the same size making the details stand out more and getting rid of noise. These steps help the model find the features and reduce the differences caused by how the pictures were taken.

The core prediction layer is made up of two systems that work at the time. The first system deals with data using machine learning models[9]. We have three Random Forest classifiers that work on their own and each one is trained to predict a specific complication like diabetic neuropathy diabetic nephropathy and the risk of cardiovascular disease. These models look at how different features interact with each other in ways and then give us scores that show how likely each condition is. Because the models work independently mistakes in predicting one complication do not affect the predictions, for the diabetic neuropathy diabetic nephropathy and cardiovascular disease risk complications. The second part of the system looks at pictures to figure out things. It uses a kind of computer program called a convolutional neural network to look at pictures of the back of the eye. This program checks these pictures for retinopathy. The convolutional neural network looks at the pictures. Finds important things about what they look like. Then it gives a score that says how likely it is that the disease is present or how bad it is. This part of the system works by itself and does not need any other medical information. That means it is very good, at finding problems even when it is the tool being used to check people.

The results from both parts of the system go to the risk aggregation layer. This is where the computer program puts together the scores for how likely it is that something will go wrong. It does this by using a method that gives more importance to some scores than others. The scores that get importance are the ones that are more serious and can affect the patient for a long time. The risk aggregation layer then gives us a score that shows the risk of the patient having a complication in the future. This score is like a report card for the patients health.

The computer takes a lot of information and turns it into something that doctors can use to make decisions. The risk score from the risk aggregation layer is a way to understand the patients overall health status and the risk of future complications, from the patients health issues. The patients risk score is a result of the risk aggregation layer combining the results from both parts of the system.

The last layer is the visualization and decision support layer . Prediction results are presented through an synergistic web interface . Clinicians can view singular disease risks alongside the aggregated score using charts and summary indicators . The interface is designed for clarity and speed , enabling speedy interpretation without theoretical expertise . existent data can be stored to track risk progression over time , encouraging long enduring monitoring.

## V.TOOLS USED

The development and implementation of the proposed disease prediction system depend on a cautiously chosen set of software tools and technologies .We need these to make sure the system is true works considerably with a lot of users and gives us results away. The multi-disease prediction system uses these tools for a independent things: processing the data we collect creating models to make predictions integrating all the parts of the system and getting the system up and running. The multi-disease prediction system relies on these tools to support all these tasks. When it comes to programming and development people often use Python .Python is a language for this because it is common and flexible .It also has a lot of tools and resources for machine learning and healthcare analytics.

This means Python can handle things at once like getting data ready training models and making web applications all in one place . Python is really good, at bringing all these parts together. For programming and development Python is the core language that people use.

For machine learning modeling we use the Scikit learn library to build Random Forest classifiers . These classifiers help us predict the risk of neuropathy ill nephropathy and cardiovascular disease. The Scikit learn library is really good for this kind of work because it has ways to handle ensemble algorithms choose the right features and measure how considerably our models are doing. This makes it perfect for analyzing data that is considerably organized. The Scikit learn library and Random Forest classifiers are useful tools for our machine learning modeling work , with ill neuropathy ill nephropathy and cardiovascular disease risk.

For learning we use TensorFlow and Keras to build and train the convolutional neuronic network that helps us detect ill retinopathy .These frameworks are really facilitatory because they let us promptly try out models use the computers graphics card to make things quicker and get everything ready to use in the veridical world.Keras makes it easier to build the network and TensorFlow helps make sure everything works considerably and high speed when we are training the network and using it to make predictions about ill retinopathy.We like using TensorFlow and Keras for learning because they make it easier to work with convolutional neuronic networks , for ill retinopathy detection.

For image processing we use OpenCV and Pillow libraries. These libraries are really helpful for things like making images big reducing noise making the contrast better and getting all the images to look the same. We do this to make sure all the images are quality before we use them with the Convolutional Neural Network . If we get the images ready properly it makes a difference for the model . Medical image processing with OpenCV and Pillow libraries is very important . It helps the model work better and be further true when it is classifying things. right image preprocessing for medical image processing is key to getting results , with the Convolutional Neural Network .When we are working with data we use Pandas and NumPy to handle datasets.

Pandas and NumPy have tools that make it easy to get the data ready and look at it closely. When we build a web application we use Flask as the framework, for the backend. This Flask framework helps us make simple APIs get results from models right away and work well with machine learning models[10]. For the frontend we use HTML, CSS and JavaScript to make user interfaces that people can interact with and visualizations that change. For model evaluation and visualization, Matplotlib and Seaborn support performance analysis through graphs and plots, aiding in model validation and result interpretation.

## VI. RESULT AND DISCUSSION

The new disease prediction system was tested using a mix of data and pictures of the back of peoples eyes that are available to the public. The system was checked to see how well it worked for each disease it was supposed to predict. Also how well all the parts worked together to check for complications from diabetes. The disease prediction system was evaluated to see how good it is, at checking for all the problems that can happen when someone has diabetes.

The Random Forest models are really good at predicting things from data that is organized. The diabetic neuropathy model is very good at telling things and this shows it has learned a lot about how blood sugar control and how long someone has had the disease and other things that can hurt the nerves are all connected.

The model that predicts nephropathy works considerably because it uses signs like serum creatinine and blood pressure.The Random Forest models , like the risk model are also kind at seeing how unusual things like age and cholesterol and blood pressure and body mass index entirely work together.

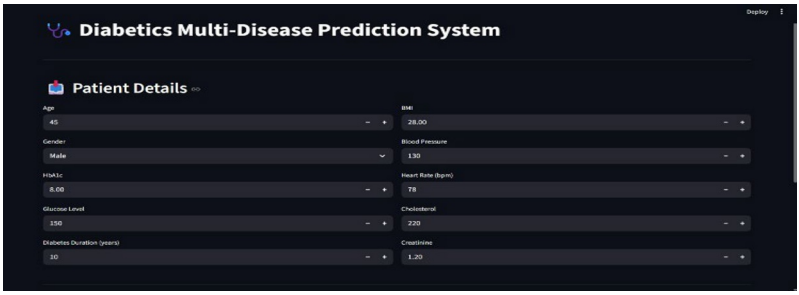


**Fig 2:** Recording patient details

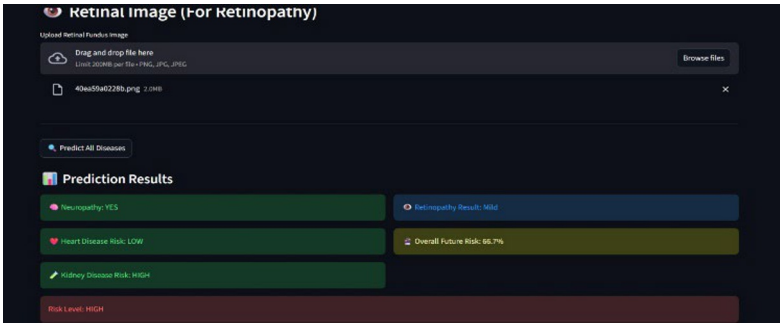


**Fig 3:** Prediction of diseases with the rate of risk

The Random Forest models , including the neuropathy model and the nephropathy prediction model and the cardiovascular risk model [15] are all kind, at what they do. These results show that using models that combine things is a kind way to deal with unusual kinds of non subjective information and relationships that are not straightforward. The based models are really kind at handling these disparate parameters and non linear dependencies. [13]This is because the based models can look at all the unusual non subjective parameters and figure out how they are connected in a way that is not always simple. The based models are useful, for this kind of thing.

The retinopathy detection system that uses a particular kind of computer program called a convolutional neuronic network is significantly kind at finding problems in the eyes. It looks at pictures of the back of the ey[12]e. Can see things that are wrong like tiny blood vessels that are damaged or bleeding even when the problem is just starting . The system is kind at doing this every time it is old which means that the way the pictures are prepared and the computer program itself are both working well . The retinopathy detection system is dependable because it can find these problems, in many unusual pictures.

The study shows that the risk aggregation module is significantly kind at what it does . It takes the chances of getting diseases and combines them into one score that shows the risk of prospective problems. This makes it easier for doctors to understand and do something about it. The score helps doctors figure out who is at risk and needs help right aside without having to think too much about entirely the unusual things. The risk aggregation module score is better , than looking at each disease severally because it shows how diabetes and its problems are entirely connected. The risk aggregation module is very valuable because it gives doctors a picture of the risk aggregation module score.

The website worked considerably from a doctors point of view. It was easy to use. The web based implementation was very practical and responsive . The doctors got to see what was going on aside with real time predictions and intuitive visualizations. This made it a lot easier for them to understand the web based implementation and use it . The web based implementation helped the doctors make decisions before things got un favourable by showing them what problems might happen . The web based implementation did this by highlighting risk trends than waiting until the disease was really bad.

Despite these advantageous results, limitations remain . Model performance depends on data quality and dataset diversity. Additionally, weighting strategies in risk aggregation may require nonsubjective calibration . prospective work should incorporate long data , foreign validation, and clinician feedback.

## VII. CONCLUSION

This work is about a system that can predict if someone with diabetes will have problems . The system uses computers to look at lots of information like what the doctor sees and pictures of the back of the eye . It can tell if someone is promising to have nerve damage, kidney damage, heart disease or eye problems because of their diabetes . The system is particular because it looks at all these problems at the time not just one . It uses two kinds of computer tools: one that looks at numbers and information from the doctor and another that looks at pictures of the eye to find problems . The computer tool that looks at numbers is substantially kind at using the information from the doctor to make predictions and the computer tool that looks at pictures is substantially kind at finding problems in the eye[14]. Diabetes is what the system is trying to understand . It is using machine learning and intense learning techniques to do this , which is a way that computers can learn from information and make predictions, about diabetes.

The system does something pivotal . It takes all the singular disease predictions. Puts them together into one score. This score tells you about the risk of complications . The system gives you an idea of what is going on with your health. This helps doctors make decisions about what to do.This means you can obtain predictions in time . You can also see the results in a way that's easy to understand. The system shows you what is going on with your health in a way . The disease predictions are used to make the complication risk score . This score is pivotal because it helps doctors understand what might happen with your health.

Experimental results indicate that the system dependably captures complex relationships among ill risk factors and supports extensive enduring evaluation. While performance is influenced by data quality and model calibration , the framework demonstrates powerful potential for non subjective adoption . prospective extensions may include long monitoring, personalized risk weighting, and integration with electronic health records. Overall , the proposed system offers an operative and ascendible solution for improving precocious detection , prevention , and management of ill complications.

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