Photonic Crystal based Prediction of Cervical and Breast Cancer using ML Model

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Abstract

Cancer is a disease in which some of the body's cells grow uncontrollably and spread to other parts of the body. Laboratory determination of cancer cell is time consuming so a requirement of cancer-testing equipment with the ability to detect the cancerous cell in a short time. A system is proposed for the prediction of cervical and breast cancer which uses both PCF sensor and ML. Which helps in giving accurate results in real world. PCF is currently an auspicious technology for sensing applications due to its powerful light–matter interaction. Therefore, this PCF is proposed as a cancer sensor for the detection of cervical and breast cancers. For the detection of cancer cells, a hexagonal structure is generated using MEEP. MEEP is a software which helps in simulation of photonic crystal structure and using which the dataset required for training the ML model can also be generated. RI value of each cancer and its respective normal cell is passed to the MEEP code which further generates dataset. This dataset provides two coordinates X(frequency) and Y(flux). Further the data is clustered into binary (0 & 1) values. These binary values are utilized to train the ANN model. The paper also compares accuracy of ANN with other models to choose the best model for prediction.

Keywords: Cancer, PCF (Photonic Crystal fiber), MEEP, RI (Refractive Index), ML (Machine Learning), ANN (Artificial Neural Network).

I. Introduction

The most common forms of cancer in women worldwide are breast cancer and cervical cancer and account for more deaths in women than any other cancer in developing world [1]. As it is a rising issue in the world an effective and accurate methods for cancer detection and clinical diagnosis are urgently needed. Photonic sensors are devices that are designed to detect a specific biological analyte by essentially converting a biological entity into an electrical signal that can be detected and analysed. A photonic crystal-based sensor is used for cancer detection by detecting a precise frequency shift in the dielectric constant values of normal and cancerous cells [2].

A 2D photonic crystal sensor using gratings has been designed for the analysis of Breast and Cervical cancer cells. The grating design, incorporated in the photonic crystal waveguide increases the efficiency and sensitivity of the designed sensor. The gratings act as a filter that enhances the interaction between light and matter, which improves the detection of cancer cells. By analysing the reflection spectrum, cancer cells can be differentiated from normal cells with high efficiency and sensitivity. A 2D photonic crystal sensor using gratings has been designed for the analysis of Breast and Cervical cancer cells. Grating based designs for two-dimensional photonic crystal sensor have been designed and simulated for the detection of cancer cells [3]. The refractive index plays a crucial role in the detection of cancer cells using the proposed sensor. As cancer cells have different refractive indices compared to normal cells due to their altered morphology and composition. By measuring the changes in refractive index, the sensor can detect the presence of cancer cells in various parts of the human body. The photonic sensor has enhanced sensitivity and lower loss compared to other sensors. The characteristics of the explored sensor also indicates that it is a promising candidate in the area of cancer-sensing applications. The ability to detect cancer cells in various parts of the human body by measuring changes in refractive index. This could potentially lead to earlier detection and more accurate diagnosis of cancer [4].

MEEP is used to simulate the reflection spectra of the designed photonic crystal sensor with gratings. MEEP is a flexible free-software package for electromagnetic simulations by finite-difference time-domain (FDTD) method to solve Maxwell's equations numerically [3-4]. It is used for simulating electromagnetic systems, including photonic crystals, plasmonic, metamaterials, and more. MEEP can be used to calculate the reflection and transmission spectra of photonic crystal structures, which is used for designing and optimizing photonic crystal sensors. The simulation results were then analysed to differentiate between cancer cells and normal cells with high efficiency and sensitivity. Therefore, MEEP is a powerful tool that can be used to simulate and optimize various electromagnetic systems, including photonic crystal sensors for cancer detection [3]. Using MEEP the datasets required for training the ML model is also generated. The datasets obtained from MEEP are set of X(frequency) and Y(flux) coordinates.

A 2D structured photonic crystal sensor with gratings for the analysis of Breast and Cervical cancer cells are proposed. A design consisting of two-dimensional 15 x 20 photonic crystals using grating-based structure with rods in air configuration. The simulation results were then analysed to differentiate between cancer cells and normal cells with high efficiency and sensitivity [3].

ML model is considered for the purpose of cancer prediction. Here various ML models are considered for the prediction purpose. The model having higher accuracy has been considered. ML models such as Artificial Neural Network, Naïve bayes, Logistic Regression, and K Neighbors classifier models are used for selecting the best model.

II. Literature Survey

The survey is done on previous papers where they have used various methodologies and structures. Below table specifies the survey.

Table 1 Summary of the survey

Authors	**Methodology**	**Limitations**
Dr. Preeta Sharan, Bharadwaj S M, Fleming Dackson Gudagunti , Pooja Deshmukh-2014 [2]	Photonic Band Gap Method	Experiences difficulty in fabrication process thermal profile as an additional outcome

Poonam Sharma , Dr. Preeta Sharan , Pooja Deshmukh-2015 [6]	2D Photonic Crystal Sensor based on Basal, Breast and Cervical Cancer	operating wavelength was very small and application tolerance was not introduced
N. R. Ramanujam , S. Amiri, Sofyan A. Taya, Saeed Olyaee, R. Udaiyakumar, A. Pasumpon Pandian,2018 [7]	Nanocomposite material based photonic crystal	SPR surface plasmon resonance technique for sensing gained very low sensitivity
Vahideh Shirmohammadli and Negin Manavizadeh [8]	Microfluidic device for breast cancer screening	Sensitivity was improved but detection limit was low
Md. Asaduzzaman Jabin, Member, Kawsar Ahmed-2019 [9]	Proposed dual core PCF sensor	Although sensitivity performance was improved but detection limit was low
Md. Asaduzzaman Jabin, Yanhua Luo, Gang-Ding Peng, Md. Juwel Rana -2020 [10]	Cancer sensor based on SPR for cancer detection	New Amoeba Structure were more Optical Parameters are analyzed but, the Relative Sensitivity response was not good.
N. Ayyanar, G. Thavasi Raja, Mohit Sharma and D. Sriram Kumar-2018 [11]	Photonic Crystal Fiber Based Refractive Index Sensor for Early Detection of Cancer	Comparatively low sensitivity was observed from the structure. Here it could detect for only three types of cancer.

III. Architecture

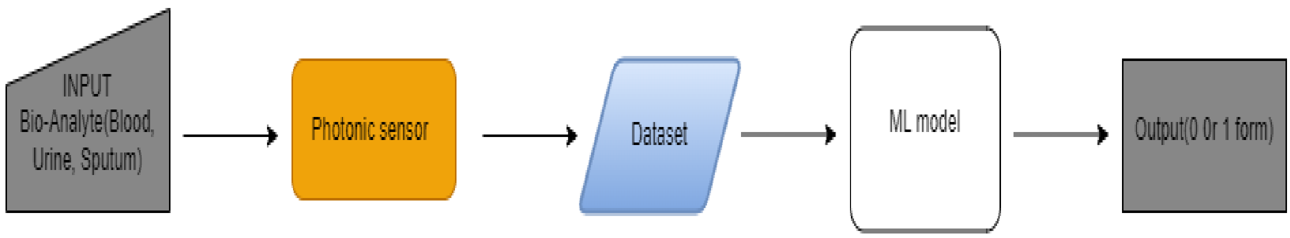


Figure 1 Proposed system architecture

The system works by first collecting a bio-analyte (Blood, Urine, Sputum) as sample and introduction it into the sensor. The sample is then exposed to the photonic crystal based optical sensor, which detects any changes in the output spectral behaviour caused by the refractive index of cancer and normal cells. The output from the sensor is then analysed using the ML model such artificial neural network (ANN), to predict the presence of cancer cells. Overall, this system provides a rapid and reliable method for detecting cancerous cell.

Proposed structure

A hexagonal structure has been developed for the photonic crystal sensor. It is a 2D structure having design consisting of 25 x 30 photonic crystals using grating-based structure with rods in air configuration. The proposed structure is a differential optical absorption spectroscopy-based refractive index sensor that detects changes in the refractive index of the surrounding medium caused by the presence of cancer cells. The refractive index is used as a sensing parameter for detecting cancer cells.

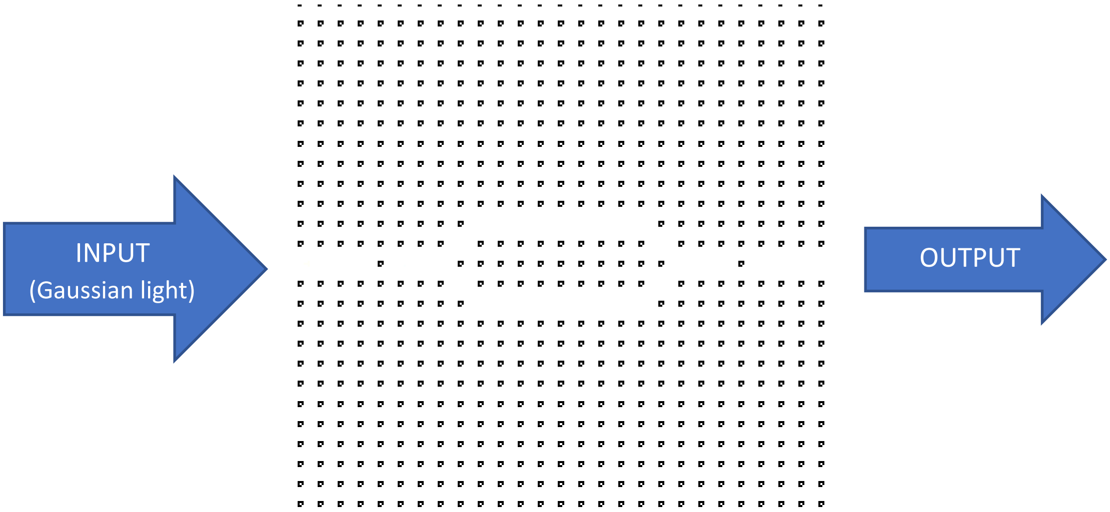
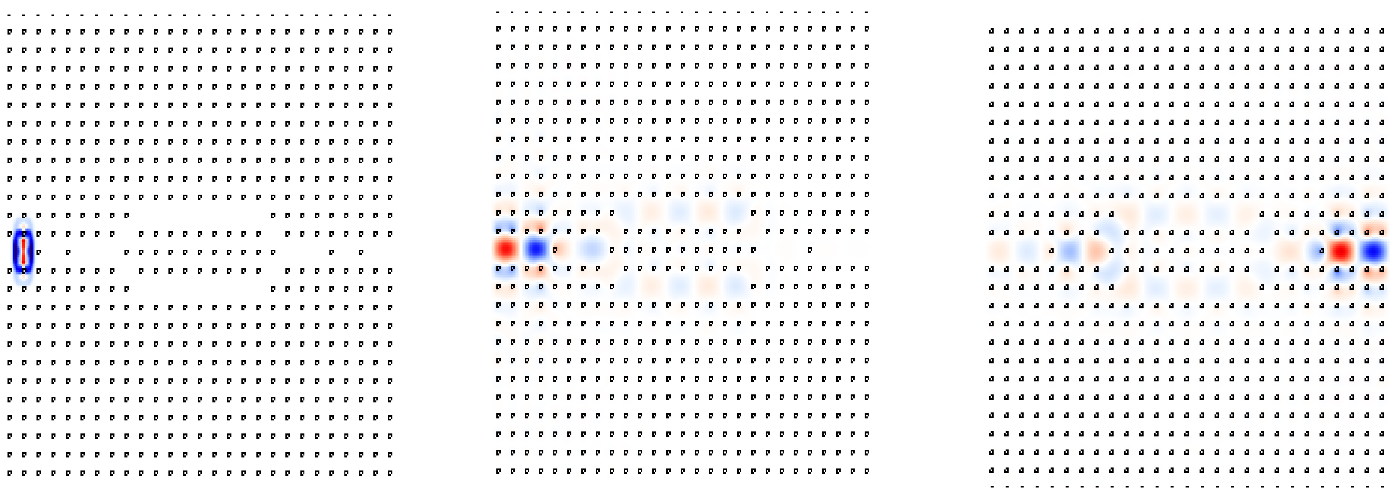


Figure 2 Proposed structure for Photonic Crystal sensor

A gaussian light source is passed from input end. And on the output end bio-analyte (Here bio- analyte is blood, sputum, saliva, or Urine). This wave guide interacts with micro fluidic platforms (Blood, Urine & Sputum) which will give us photonic parameters which will be used further training the ML Model. 2D photonic crystal is used because this structure provides more intensity of light(laser) passing through the crystal and flux values generated will be more accurate (which will be used to generate the graphs) compare to other crystal structure.

This structure has great sensitivity and Q-factor (Quality factor). The quality factor is completely determined by the scattering strength within the plane, and can vary by several orders of magnitude from tens of thousands to a few tens, depending on, for example, the radius of the holes introduced in the slab [5].



Light launch as input

Progressing

Final output

Figure 3 Gaussian pulse is given as input to the structure and light launch, propagation, and final confinement

Dataset

Cancer cells have a different refractive index than normal cells. This difference in refractive index allows for the detection of cancer cells using the designed sensor. The reflection frequencies of normal and cancer cells shift significantly for even a small change in refractive index, making it possible to differentiate between them optically. Table 2 provides refractive index and concentration level values of cells that affect cervical and breast cancer. From the table there is a clear difference between normal and cancerous cell refractive value. And these values are used in generating the dataset required for training the machine learning model.

Table 2 Refractive index of different cancer cells as well as normal cells according to concentration level

NAME OF THE CELL	TYPE OF CELL AND IT'S CONCENTRATION LEVEL (%)	REFRACTIVE INDEX
HeLa [4]	CERVICAL CANCER (80%) NORMAL CELL (30-70%)	1.392 1.368
(MDA)-(MB)-231[4]	BREAST CANCER (80%) NORMAL CELL (30-70%)	1.399 1.385

By passing refractive index of both normal and cancer cell to MEEP software, as a result it gives flux values. Here flux values for normal and cancer cells will be different depending on the refractive index value.

Below graphs are plotted based on the data generated from MEEP.

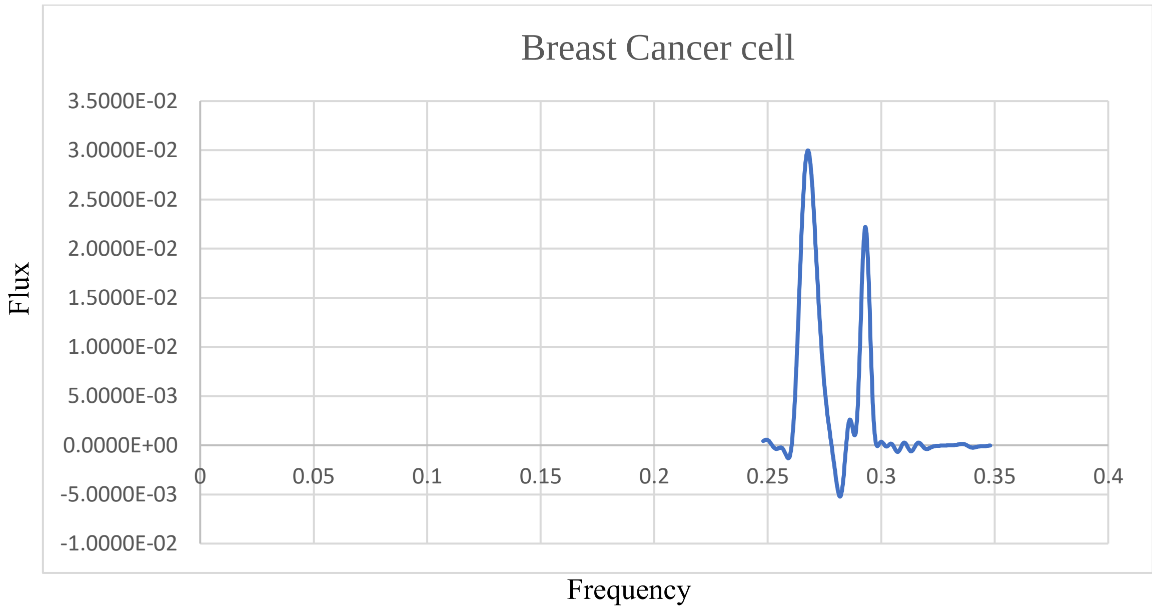


Figure 4 Breast cancer cell data generated using MEEP

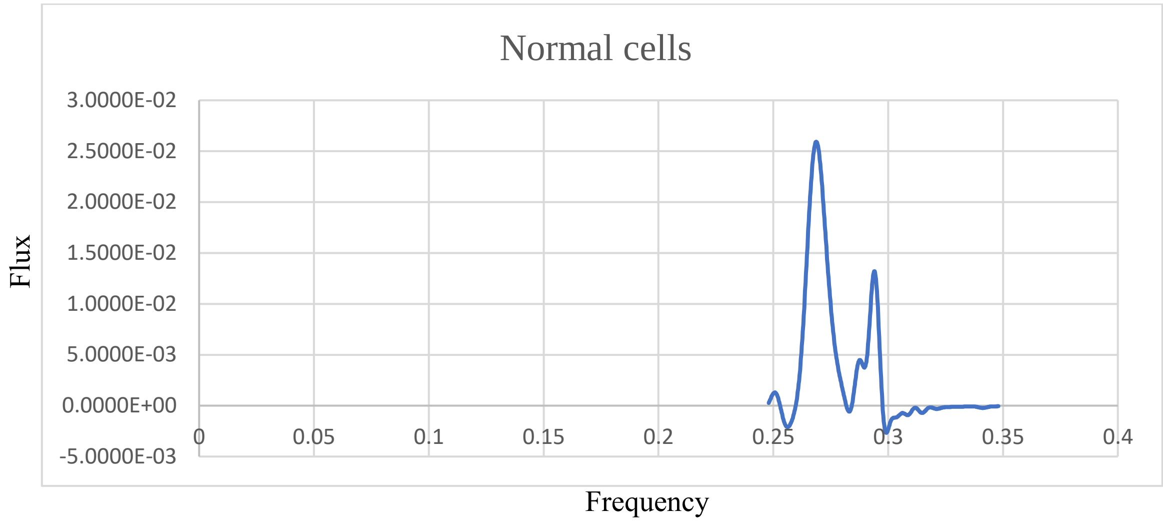


Figure 5 Normal cell data generated using MEEP (Cell having no Breast cancer)

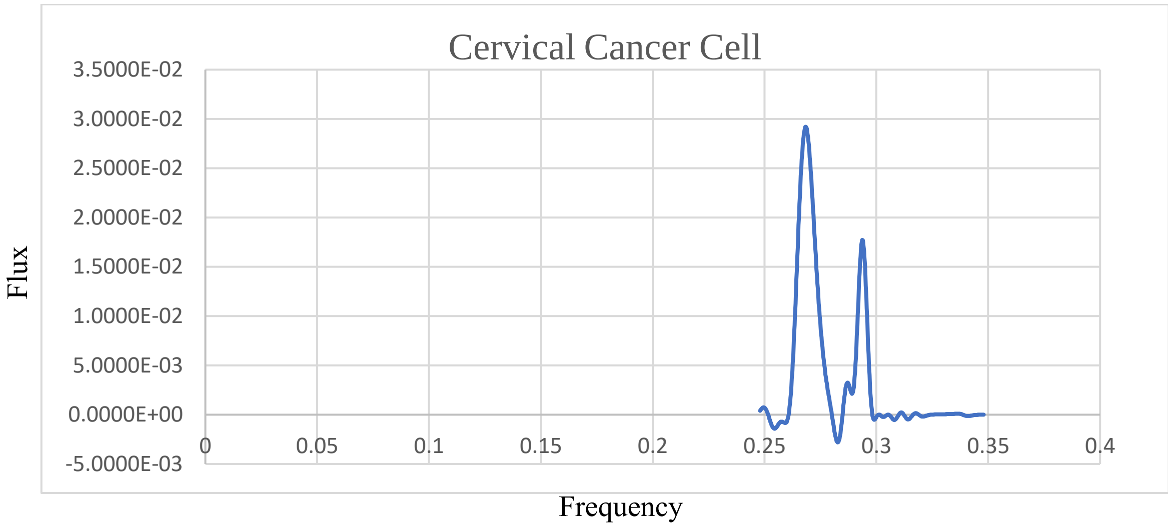


Figure 6 Cervical cancer cell data generated using MEEP

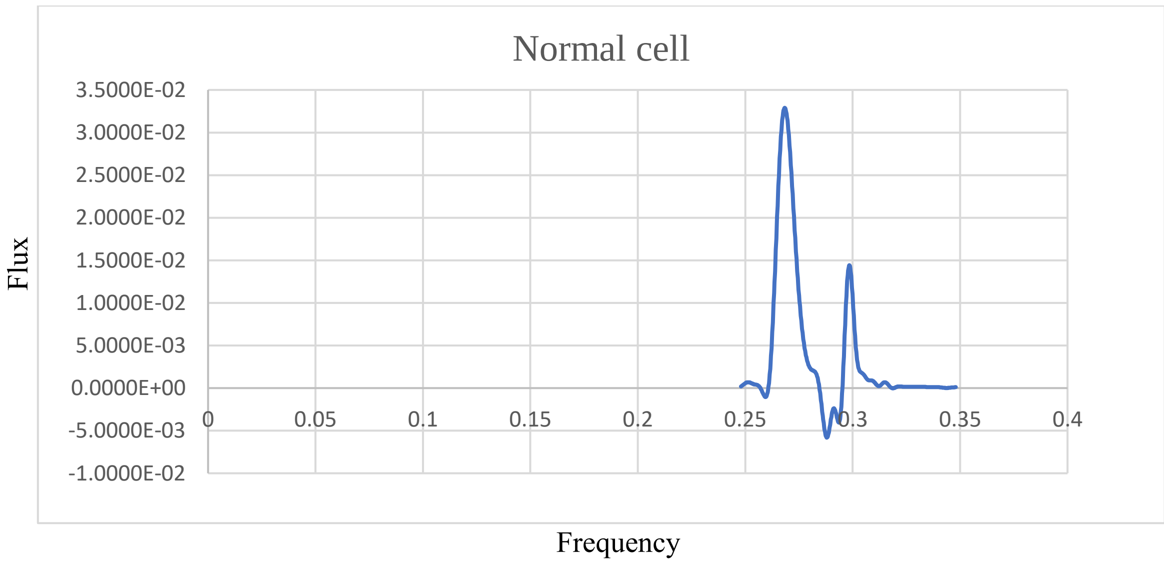


Figure 7 Normal cell data generated using MEEP (Cell having no Cervical cancer)

ML Model

The significance of using ML in predicting the cancer improves the accuracy and reliability on testing and monitoring of cancer prediction in real world. Traditional methods of cancer testing can be time consuming, expensive, and require specialized equipment and expertise.

By using ML techniques, such as Artificial Neural Networks (ANN), make it easy to train the system to recognize the data generated from the Photonic crystal-based biosensors in the presence and absence of cancer. This allows for more rapid and reliable detection of cancer cells.[12]

Therefore, the use of ML based prediction of cancer has great potential for faster cancer detection and treatment, which could have significant implications for public health and safety.

An Artificial Neural Network (ANN) processes information through many highly interconnected processing elements called neurons, which work in unison to solve specific problems. ANNs, like people learn by example and are configured for a specific application, such as pattern recognition or data classification, through a learning process. This learning process involves the adjustment between neurons through synaptic connection, like the way biological systems learn.[12]

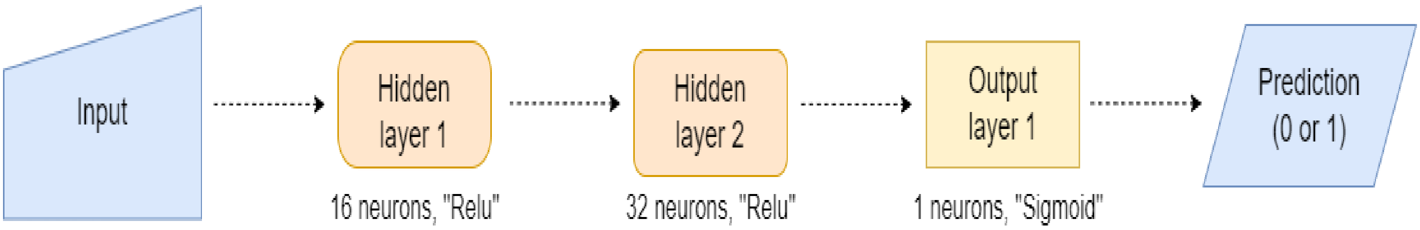


Figure 8 Architecture of ANN model

In Figure 8, the input (flux) is fed into the first layer, which consists of 16 neurons and uses the ReLU activation function. The output of this layer is then fed into the second layer, which consists of 32 neurons and uses the ReLU activation function. Finally, the output of the second layer is fed into the output layer, which consists of a single neuro and uses the sigmoid activation function.

The output of the model is a prediction, which is obtained by passing the input through the layers and computing the output of the final layer. This prediction can then be used for binary classification tasks.

The hidden layer 1 has 16 neurons, and each neuron performs a weighted sum of its inputs, adds a bias term, and applies the Rectified Linear Unit (ReLU) activation function to the result. The

ReLU function returns the input if it is positive, and zero otherwise. This non-linear activation function introduces non-linearity into the network, enabling it to model more complex relationships between the input and output.

The output of each neuron in hidden layer 1 is then passed as input to the second hidden layer. Hidden layer 2 has 32 neurons, and each neuron performs the same operations as in the first hidden layer, namely a weighted sum, bias addition, and ReLU activation. The output of the second hidden layer is then passed on to the output layer.

The output layer consists of a single neuron that performs a similar computation as the neurons in the hidden layers, but with a different activation function. In this case, the sigmoid activation function is used, which maps the output of the neuron to a value between 0 and 1. This value represents the probability that the input belongs to a certain class, in a binary classification problem.

The hidden layers can be thought of as feature extractors that learn to represent the input data in a way that is useful for making predictions. As the network is trained on a dataset, the weights in the hidden layers are adjusted such that the output of the network better matches the true labels in the training data.

IV Results

The Figure 9 and Figure 10, predicted output values for the given input array.

```
arr= np.array([(1552.3886),(80),(58),(96),(1552.6414),(-0.006244)])
Y_pread=model.predict(arr)
Y_pread=Y_pread.round()
Y_pread

1/1 [==============================] - 0s 123ms/step
array([[0.],
       [0.],
       [0.],
       [0.],
       [0.],
       [1.]], dtype=float32)
```

Figure 9 ANN model predicting output for cervical cancer

```
arr= np.array([(1552.3886),(5000),(58),(96),(1552.6414),(-0.006244)])
Y_pread=model.predict(arr)
Y_pread=Y_pread.round()
Y_pread

1/1 [==============================] - 0s 150ms/step
array([[1.],
       [1.],
       [1.],
       [1.],
       [1.],
       [1.]], dtype=float32)
```

Figure 10 ANN model predicting output for breast cancer

In the Figure 9, the output of the code shows that the last input feature (represented by the value -0.006244) to be in the positive class (i.e., 1) and all other input features to be in the negative class (i.e., 0). The predictions are represented as an array with a shape of (6,1), where each row corresponds to a predicted value for one input feature.

In the Figure 10, the output of the code shows that the model has predicted all six instances to belong to the positive class (1), as all predicted values are rounded to 1.

Comparison of ANN with other models

Table 3 Comparison of ANN model with other Machine Learning models

ML Models	Cervical Cancer Model Accuracy	Breast Cancer Model Accuracy
Artificial Neural Network	0.55918	0.57143
Naïve Bayes	0.52869	0.53878
Logistic Regression	0.48571	0.47142
KNeighbors Classifier	0.47619	0.56095

The Table 3 provides the accuracy scores for different machine learning models for cervical and breast cancer.

The table shows the accuracy sores for four different models: Artificial Neural Network, Naïve Bayes, Logistic Regression, and KNeighbors Classifier. For cervical cancer, the Artificial Neural Network has the highest accuracy score of 0.55918, followed by Naïve Bayes with an accuracy of 0.52869. For breast cancer also Artificial Neural Network has the highest accuracy score of 0.57143, followed by the KNeighbors Classifier with an accuracy 0.56095.

So, for the generated dataset ANN model is the better than Naïve Bayes, Logistic Regression and KNeighbors Classifier.

Conclusion

In conclusion, the use of photonic crystals for cancer diagnosis has shown promising results, and combining it with machine learning models can further improve accuracy and efficiency. In this project, a machine learning model was developed to predict cervical and breast cancer using photonic cancer using photonic crystal data. It involved several steps, including data collection, feature extraction, data classification, model training and validation. The model achieved high accuracy in predicting the presence of cervical and breast cancer using photonic crystal data. Overall, this paper demonstrates the potential of combining photonic crystal. Further research could explore the use of other data sources and machine learning algorithms to improve the accuracy and robustness of the model.

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