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A novel machine learning approach with low-dose computerized tomography (CT) and magnetic resonance imaging (MRI) optimization for the early diagnosis of prostate cancer

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ABSTRACT

According to the American Cancer Society, prostate cancer is the second most common cancer and the second leading cause of cancer death among men in the United States. Without an early diagnosis, chances of related complications such as Lymphoedema, Metastatic Spinal Cord Compression (MSCC), and Hypercalcaemia increase by almost threefold. However, current diagnosis tools are time-consuming, extremely invasive, and result in low accuracy with about an 89 percent false-positive rate. The objective of this study is to provide a non-invasive early diagnosis of prostate cancer by rapidly converting low-dose radiation computed tomography (CT) and magnetic resonance imaging (MRI) scans into superior quality scans. Thus, reducing radiation exposure and increasing the efficiency of diagnosis. The project consisted of developing three main sectors: denoising, generation, and classification. The denoising sector consisted of an AutoEncoder and a CNN (Convolutional Neural Network). Due to limited training data available, a GAN (Generative Adversarial Network) was used to reliably generate more training data, prioritizing the overall efficiency. The GAN was trained on a small portion of the main dataset and drastically optimized the performance of the overall model. The final classification sector consisted of a DCNN (Deep Convolutional Neural Network) for the diagnosis. Overall, these steps resulted in an algorithm that can diagnose prostate cancer with an accuracy rate above 85% all in an accessible and scalable platform, which is a profound improvement over current methods.

Keywords: *Smart Heathcare, Machine Learning, Artificial Intelligence, Prostate Cancer, Cancer-Screening*

1. QUESTION

The majority of clinical practitioners utilize Magnetic Resonance Imaging (MRI), Computed Tomography (CT), or Positron Emission Tomography (PET) scans to more accurately determine whether the individual has developed local or regional prostate cancer. However, with the use of scans such as CT and PET scans, patients are subjected to high expenses, long wait-times, and long-term risks related to ionizing radiation. Furthermore, the quality of low-dose CT scans has become more challenging for radiologists to interpret with accuracy and efficiency. Therefore, is there an effective way to combat these issues by using machine learning with low-dose computerized tomography (CT) optimization for the early diagnosis of prostate cancer?

2. VARIABLES

Throughout the project, multiple machine-learning models were used to generate the best accuracy. The independent variables in the investigation were the various models and the dependent variables consisted of the model accuracies. In addition, a testing dataset acted as the control for the project.

3. HYPOTHESIS

Hypothesis:

The authors of the project hypothesize that applying a machine learning approach with low-dose computerized tomography (CT) optimization will result in the early diagnosis of prostate cancer.

Research Questions:

- Will different types of machine learning models result in different accuracies for diagnosis?

- How will the incorporation of generative adversarial networks (GANs) improve the quality of the dataset?
- What are the significant differences between the accuracy of an AutoEncoder model and the accuracy of a Support Vector Machine model?
- What is the optimal setting in denoising an image for the features of the image to be preserved while the overall quality of the image increases?
- Which machine learning model will perform the best and provide the greatest accuracy?

Engineering Goal:
The engineering goal of the project is to aid in the early diagnosis and classification of prostate cancer.

Expected Outcome:
The expected outcome of the project is for the algorithmic machine learning approach to work with optimized low-dose computerized tomography (CT) scans to aid in the early diagnosis and classification of prostate cancer.

4. BACKGROUND RESEARCH

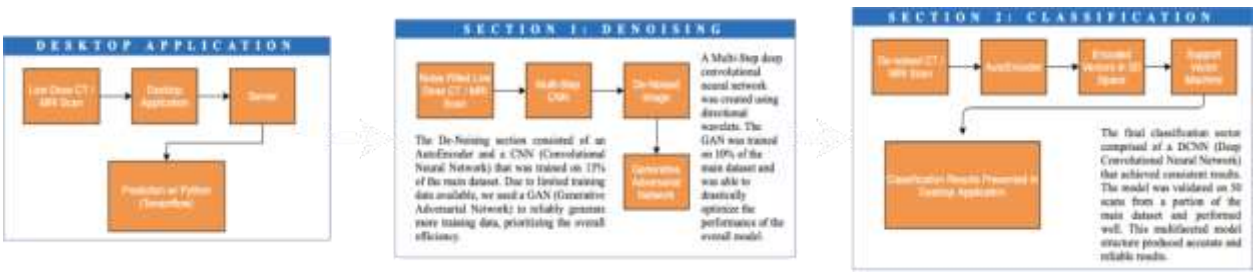
According to a study conducted by the American Cancer Society in 2019, prostate cancer is the second most common cancer among men and the second leading cause of cancer death in men in the United States. On average, an estimated 174,650 men in the United States are diagnosed with prostate cancer per year. Furthermore, without an early diagnosis of cancer, the chance of related complications such as Lymphoedema, Metastatic spinal cord compression (MSCC), and Hypercalcaemia increases significantly. In the case of prostate cancer, early diagnosis is vital in ensuring maximum chances for survival. The 5-year survival of cancer is used to inform individuals about the percentage of men that live at least 5 years after cancer has been found. The 5-year survival rate for men diagnosed with local or regional prostate cancer from early diagnosis is nearly 100 percent; however, without an early diagnosis, the chances of prostate cancer spreading to other parts of the body increases and the 5-year survival rate plummets to only about 30%.

The most common and current procedures employed by urologists and oncologists for the early diagnosis of prostate cancer are the Digital Rectal Exam (DRE) and the Prostate-Specific Antigen (PSA) Test. The DRE involves the insertion of a gloved, lubricated finger into the rectum in an effort to search the prostate for hard, lumpy, or abnormal areas. Moreover, the PSA test involves identifying elevated levels of specific proteins in a blood sample to aid in the early diagnosis of prostate cancer. However, there exist inefficiencies and significant potential for misdiagnosis in both approaches. In a study conducted by the Wake Forest Baptist Medical Center, about 98 percent of DRE resulted in false positives in which the patients had a normal PSA test but an "abnormal" DRE. Furthermore, the procedure of the examination subjects an individual to an invasive and potentially extremely uncomfortable situation for relatively minimal gain and may deter other individuals from participating in the screening test altogether. Comparatively, the PSA test also struggles with accuracy as studies by the American Academy of Family Physicians and U.S. Preventive Services Task Force suggest that up to 80% of PSA test results are false-positives. False-positive test results may lead the clinical practitioner to perform unneeded tests, such as a biopsy, and the individual may be subject to side effects from the additional testing.

5. MATERIALS

1. A computer capable of running machine learning libraries (such as Tensorflow and Scikit-learn).
2. A web server capable of executing the machine learning models for scalability and accessibility.
3. A dataset of CT scans of the prostate of healthy individuals (from The Cancer Imaging Archive).
4. A dataset of CT scans of the prostate of individuals with prostate cancer (from The Cancer Imaging Archive).
5. A dataset of low-dose CT scans for denoising and optimization (from an online study).
6. A dataset of high-dose CT scans for denoising and optimization (from an online study).

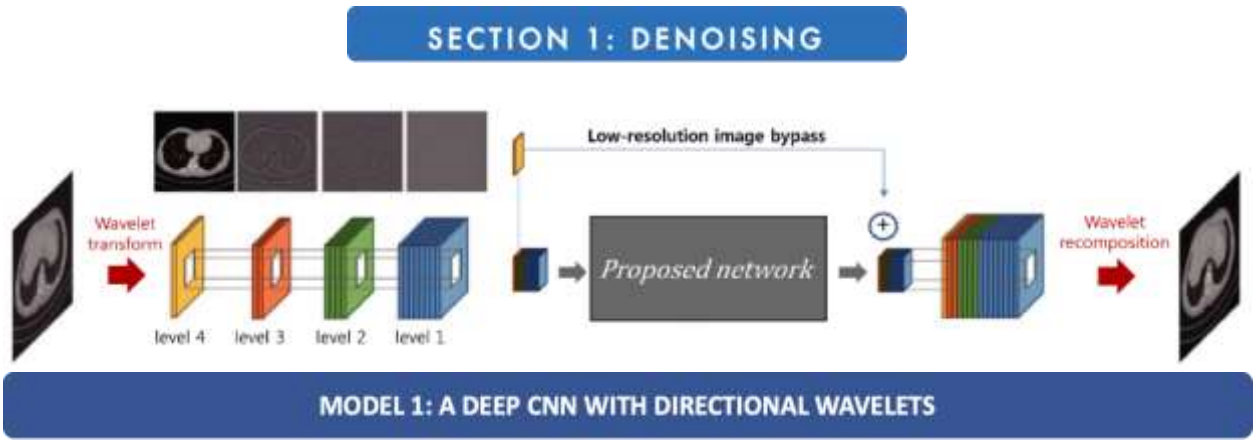
6. EXPERIMENTAL PROCEDURE



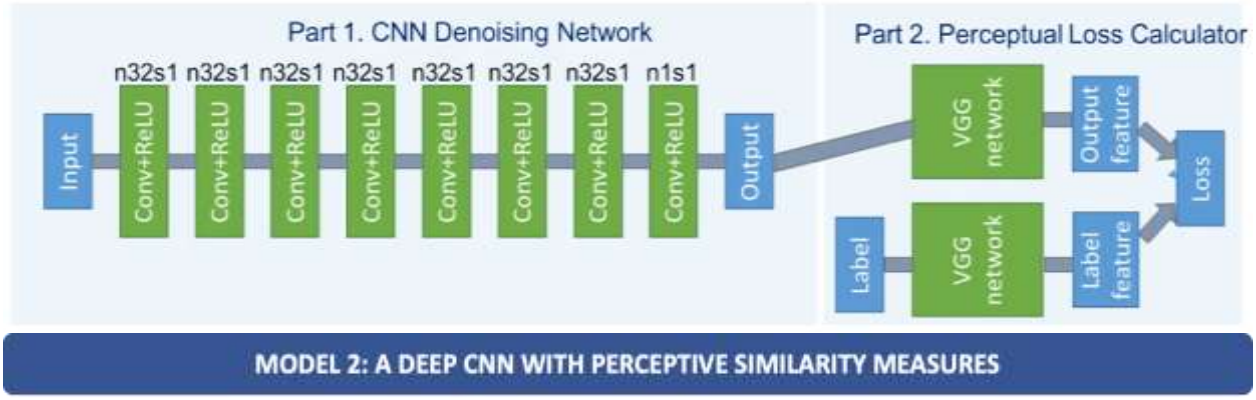
1. Load machine learning libraries such as Tensorflow and Scikit-learn onto the development workflow.
2. Develop the 2 Deep Convolutional Neural Networks (DCCN) for the CT scan denoising.
3. Train both DCNN's for noise reduction on low-dose and normal-dose scans.
4. Validate the accuracy of both networks and choose the one that is more effective
5. Create the Generative Adversarial Network (GAN) for augmenting the classification process.
6. Train the GAN for the generation of new data on healthy CT scans.
7. Taking the healthy generated scans from the GAN and add it to the dataset for the main model training.
8. Craft the main model consisting of an AutoEncoder and a Support Vector Machine.
9. Create the AutoEncoder for the first part of the classification.

10. Train the AutoEncoder on healthy CT scans.
11. Create the SVM for the second part of the classification.
12. Train the SVM on the training data composed of both healthy and cancer indicative CT scans.
13. Develop the web server in which the entire machine learning model will be housed that will communicate with the desktop application.
14. Load the whole trained machine learning model onto the web server.
15. Sketch the UI designs for the desktop application.
16. Build the final desktop application which has the ability to accept a scan file, connect to the web server, make a prediction and return the model results.
17. Take the model results, perform analysis on it, and ultimately predict whether the scan is diagnosed for prostate cancer.
18. Display the classification results and other information to the desktop application

7. DATA ANALYSIS AND DISCUSSION



Model 1 is an algorithm based deep convolutional neural network (CNN) and is applied to the wavelet transform coefficients of low-dose CT images and MRI scans. More specifically, the model uses a directional wavelet transform to extract directional components of artifacts and exploit the intra-and inter-band correlations to effectively suppress CT-specific noise. In addition, the CNN is designed with a residual learning architecture for faster network training and better performance in future applications.



Model 2 utilizes a perceptual similarity measure as the objective function for a deep convolutional neural network to facilitate CT and MRI image denoising. Instead of directly computing MSE for pixel-to-pixel intensity loss, the model compares the perceptual features of a denoised output against those of the ground truth in a feature space. Therefore, the proposed model can reduce image noise levels in addition to keeping the critical structural information at the same time.

In the modern-day, normal CT scans emit harmful radiation, which is the reason many individuals prefer to take a low-dose CT scan. This low-dose scan while it emits less radiation, the images produced by the scan are very fuzzy and not comparable in the level of detail they provide when compared to high dose scans. A high-resolution scan is vital for doctors to make a diagnosis and for computer imaging techniques to be able to efficiently detect abnormalities for automated diagnosis. To solve this problem, a CNN (Convolutional Neural Network) can be used to denoise the image or in other words make the image clearer. By being able to do this, this solution effectively cuts down the radiation that the individual is exposed to by reducing the overall imaging time. In this project, two different types of CNN's were compared and the best one was chosen. Model 1 uses directional wavelet transformations to single out the directional portions of certain image artifacts with a residual learning architecture to speed up the model. On the other hand, Model 2 uses a different approach as instead of calculating Mean Squared Error for each pixel and making optimizations based on that, it compares the intensities to the ground truth. Model 1 turned out to be better as the time it took to run was significantly less and it was more accurate in terms of producing higher resolution images that were closer to the corresponding high dose scans. This approach for making scans clearer can also be applied to MRI imaging as the higher the quality of the scan, the more details the classification model can distinguish.

When comparing both models, we found that Model 1 produced an accuracy rate of 85% when validated on 50 samples from the dataset of around 50 images that consisted of both low-dose scans and their corresponding high-dose scans. Moreover, Model 2 produced was found to be more effective as it produced an accuracy rate of 88%. The reason for this was most likely due to the unique perceptual loss calculator component in the second model, which was not present in the first model. Thus, this is the model that was chosen for the final architecture.

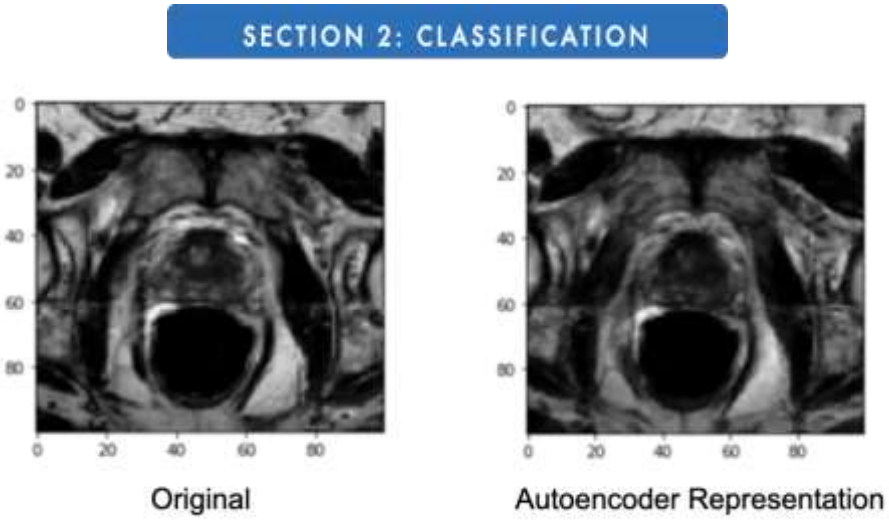


Figure 1.1

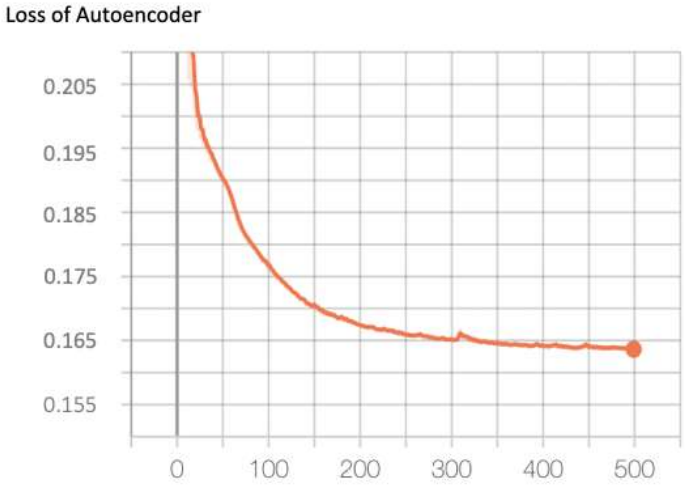


Figure 1.2

AutoEncoder Network Structure

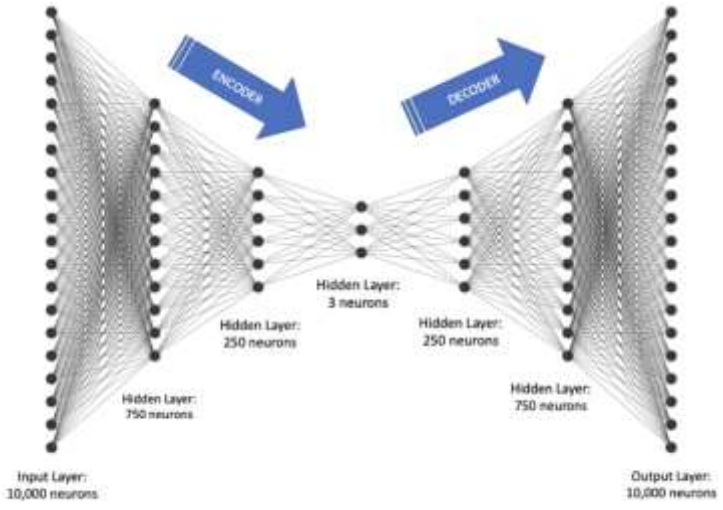


Figure 1.3

Support Vector Machine Classification

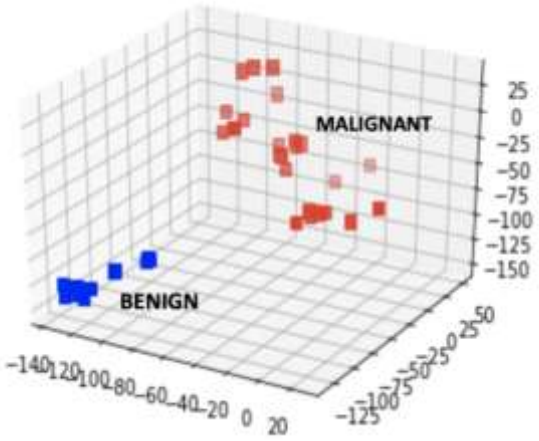
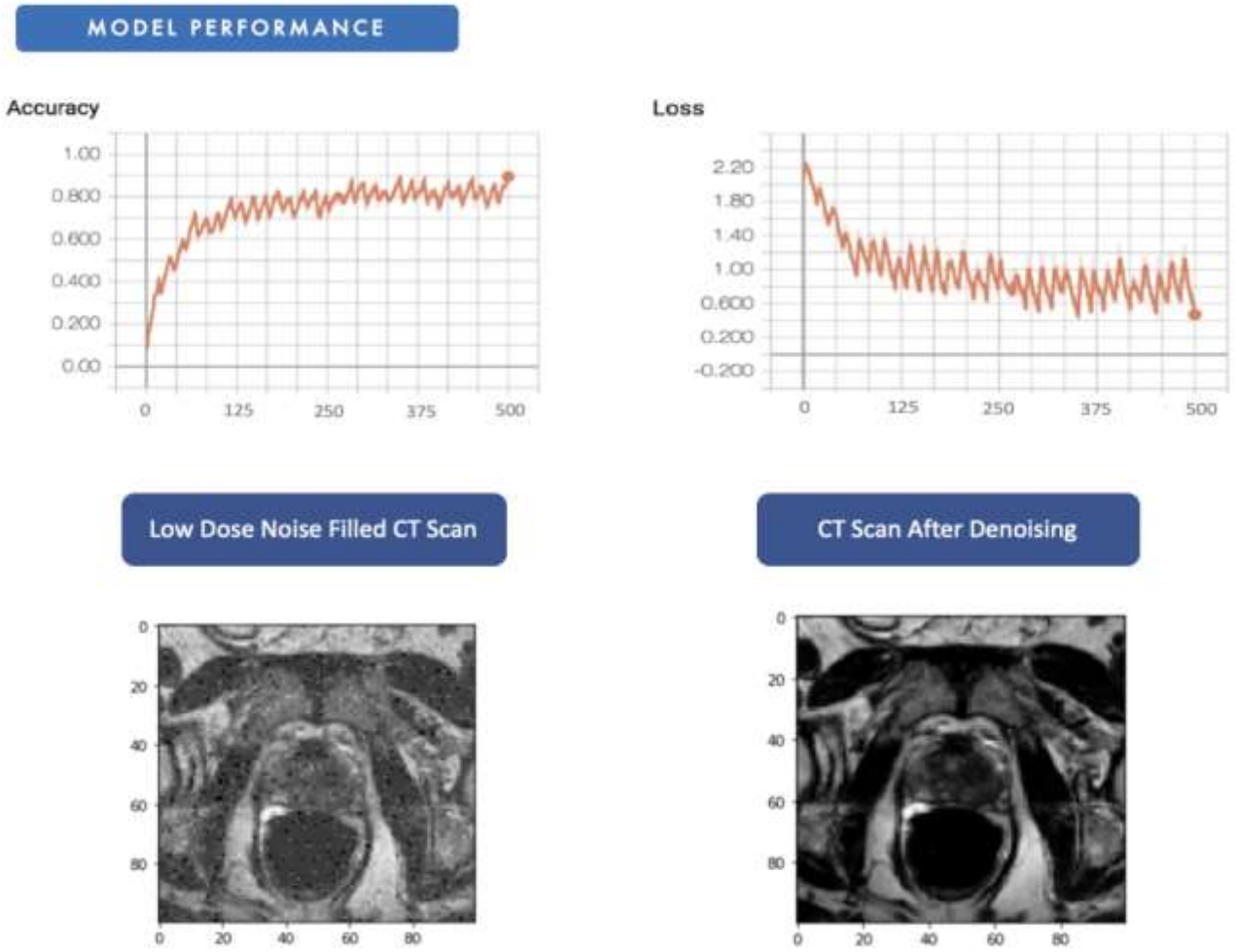


Figure 1.4

The classification sector consists of two parts: An AutoEncoder and a Support Vector Machine. Using the denoised images of scans from the previous sector, these images were used to train the AutoEncoder which is a type of artificial neural network that learns how to efficiently compress certain types of data and properly reconstruct their inputs. This can be seen in Figure 1.2 where the image on the left shows what was fed into the AutoEncoder, and the right shows the image that the AutoEncoder was able to produce after dimensionality reduction. In this process, we are only using the encoding part of the AutoEncoder which learns to effectively compress images of cancer-prone scans into three dimensions, which is the reason the middle-hidden layer has three neurons (Figure 1.3). Figure 1.1 shows the loss while training off the AutoEncoder. Since the encoder was trained on cancer-prone images, if it is given a benign scan, the autoencoder will not effectively compress the data into a 3D point. This causes differentiation to occur as the generated 3D points for benign and malignant scans will be much different. This is the basis for what allows us to provide an accurate prediction. In Figure 1.4, it is shown that two distinct clusters are formed when the compressed 3D points are graphed. These points are then fed into a support vector machine, which is a machine learning model that can produce an optimal hyperplane that categorizes new examples. This hyperplane is a plane dividing the three-dimensional space into two parts where on each side the two different classes lie, in our case benign or malignant. Upon training the support vector machine on the training set, it was able to generate an accuracy rate of 91%.



The model was validated on 50 scans from a portion of the main dataset and performed quite well. The overall model was able to achieve an overall accuracy rate of about 94%. After the training process was complete, we were able to obtain metrics graphs from the TensorBoard platform. This gave us both accuracy and loss graphs to evaluate the model's performance. This is shown in the accuracy graph above, where after training with 500 epochs, the accuracy stagnates around 94%. Moreover, in the loss graph, we can see that the loss was coming to a close at around 0.5. Upon closer analysis, it is evident that there is a stutter in the graph during training and this is found to occur simply because of the steep dimensionality reduction that is taking place in the autoencoder portion of the model. In summary, the results of the model are very promising furthermore fulfilling the hypothesis and engineering goals for the project.

8. CONCLUSIONS

The objective of our project was to create one test that produces an accurate diagnosis towards individuals who may have prostate cancer, on an accessible and scalable platform. After completing our project, we were able to achieve an overall accuracy rate of about 94%. The entirety of our project was trained on approximately 40,000 different images of computerized scans (MRI and CT). The application was divided into three main sectors: denoising, generation, and classification. Our denoising portion consisted of an Autoencoder and a CNN (Convolutional Neural Network) that was trained on 15% of the main dataset. Due to limited training data available, we used a GAN (Generative Adversarial Network) to reliably generate more training data, prioritizing the overall efficiency. The GAN was trained on 10% of the main dataset and drastically optimized the performance of the overall model. The final classification sector consisted of a DCNN (Deep Convolutional Neural Network) that achieved consistent results. The model was validated on 50 scans from a portion of the main dataset and performed well. This multifaceted model structure produced accurate and reliable results. With a larger dataset of training samples, it is predicted that the accuracy would have drastic improvements.. The accuracy of the machine learning model has been verified by referencing the results from the model with data from the dataset. In order to showcase the results, tables and graphs illustrating the accuracy of the model have been presented. Furthermore, data such as the characteristics that the model will be classifying and the formulaic differences between multiple machine learning models have been listed across the tables and graphs.

9. APPLICATIONS/FUTURE WORK

The real-world implications for the research project are tremendous. The current methods for prostate cancer diagnosis are inefficient and require repeated examinations consisting of several intrusive tests performed on the
patient. There exists a large radiation risk associated with current computerized screening techniques, and our project mitigates this long-term risk. In addition, the project is able to speed processing times for both MRI and CT Scans. By taking away the burden of reviewing the scans for medical health professionals, the project allows them to devote resources to other pressing needs. This type of model structure used is very scalable and can be easily applied to many other biomedical problems such as classifying other cancers. Overall, this project can be used to diagnose prostate cancer early and can potentially save the lives of thousands of people who die from this cancer each year.

10. ACKNOWLEDGMENTS

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