**Speech for Prithoy Chandra Roy (Slides 1-5)**

**Slide 1: Introduction**  
Hello, everyone. Our project is called *Melanoma Skin Cancer Detection*, supervised by Dr. Md. Asraf Ali. I am Prithoy Chandra Roy, and I will present the first part of this project. My teammate, Azminur Rahman, will explain the second part.  
In this project, we used deep learning to detect melanoma, a dangerous type of skin cancer, from images. Detecting melanoma early can save lives by helping patients get treatment sooner.

**Slide 2: Project Overview**  
Our goal was to create a machine learning model that could detect melanoma accurately and quickly using images.  
We chose a Convolutional Neural Network, or CNN, because it is very good at analyzing images. We trained our model on 10,000 images of skin lesions.

**Slide 3: Dataset and Validation**  
We got the images from Kaggle, a trusted source for datasets. This dataset had 10,000 high-quality images.  
To ensure the data was useful, we checked for accuracy, consistency, and completeness. Then we divided the data into training and testing sets to see how well the model works.

**Slide 4: Preprocessing and Feature Extraction**  
Before training the model, we resized all images to 128x128 pixels. This made them the same size. We also normalized the pixel values to make training faster and more stable.  
The CNN automatically extracted important features from the images, like patterns and shapes, making the process faster and more accurate.

**Slide 5: Model Training and Evaluation**  
Our CNN has the following structure:

1. **Convolutional Layers:**
   * We used four layers, each with filters of size 32, 64, 128, and 256. These layers find patterns like edges and textures.
2. **Max-Pooling Layers:**
   * After each convolutional layer, we used max-pooling to reduce the image size, keeping only the most important features.
3. **Fully Connected Layers:**
   * The flattened output from the previous layers is passed to a dense layer with 256 neurons. The final layer has one neuron and uses a sigmoid function to predict if the image shows melanoma or not.

This design helped us create a strong model for accurate predictions. Now, Azminur Rahman will explain the results and their meaning.

**Speech for Azminur Rahman (Slides 6-9)**

**Slide 6: Model Training and Evaluation**  
Thank you, Prithoy. I will now talk about how our model worked and how we tested it.  
Our CNN has:

1. **Four Convolutional Layers:**
   * These layers use filters to find patterns. Each layer uses more filters: 32, 64, 128, and 256.
2. **Max-Pooling Layers:**
   * These reduce the size of the images, keeping only the most important details.
3. **Fully Connected Layers:**
   * After the images are processed, the dense layer predicts if the image shows melanoma.

We tested our model using accuracy, precision, recall, and F1-score. These metrics tell us how well the model performs.

**Slide 7: Confusion Matrix Analysis**  
The confusion matrix helps us understand the model’s results:

* **True Positives:** Melanoma cases the model correctly identified.
* **True Negatives:** Non-melanoma cases correctly identified.
* **False Positives:** Non-melanoma cases wrongly predicted as melanoma.
* **False Negatives:** Melanoma cases the model missed.

It is very important to reduce false negatives because missing a melanoma case can delay treatment and harm patients. This analysis helps us improve the model.

**Slide 8: Results and Discussion**  
Now, let’s discuss the results:

* **Performance:**
  + The CNN achieved **89% accuracy**, while the SVM model only reached **82% accuracy**. This shows that CNN is better for this task.
* **Confusion Matrix Results:**
  + The CNN correctly predicted 443 melanoma cases and 451 non-melanoma cases. However, it missed 57 melanoma cases (false negatives) and wrongly predicted 49 non-melanoma cases as melanoma (false positives).
  + The SVM had more errors, with 91 false negatives and 87 false positives.
* **Graphs:**
  + The accuracy graph shows that the CNN’s training accuracy reached almost 100%, while the validation accuracy stabilized at 90%.
  + The loss graph shows the training loss decreased consistently, meaning the model learned well. However, the validation loss slightly increased, which suggests some overfitting.

These results prove that CNN is effective in detecting melanoma.

**Slide 9: Conclusion and Future Recommendations**  
To finish, here are our key points and recommendations:

* **Key Findings:**  
  The CNN model worked better than the SVM model in detecting melanoma.
* **Future Recommendations:**
  1. Use a larger and more diverse dataset to improve performance.
  2. Apply transfer learning to use pre-trained models for better accuracy.
  3. Include medical knowledge to refine the model’s predictions.
* **Impact:**  
  Using this model in real healthcare settings can help doctors detect melanoma early, save lives, and reduce their workload.

**Closing Statement:**  
Thank you for listening. We are happy to answer your questions.