Model summary:

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_9 (Conv2D)           (None, 30, 30, 256)       7168

 max_pooling2d_9 (MaxPooling  (None, 15, 15, 256)      0
 2D)

 dropout_9 (Dropout)         (None, 15, 15, 256)       0

 conv2d_10 (Conv2D)          (None, 13, 13, 128)       295040

 max_pooling2d_10 (MaxPoolin  (None, 6, 6, 128)        0
 g2D)

 dropout_10 (Dropout)        (None, 6, 6, 128)         0

 conv2d_11 (Conv2D)          (None, 4, 4, 64)          73792

 max_pooling2d_11 (MaxPoolin  (None, 2, 2, 64)         0
 g2D)

 dropout_11 (Dropout)        (None, 2, 2, 64)          0

...
Total params: 384,455
Trainable params: 384,455
Non-trainable params: 0
```

what the approach used to solve the problem and the reason for taking up the approach?

Solution:

The approach I employed to solve the problem of cancer cell detection was a Convolutional Neural Network (CNN), implemented using Google Colab. CNNs are a type of deep learning model that has proven to be highly effective in various image analysis tasks, including medical image analysis.

I chose the CNN approach for several reasons:

1. Image analysis capabilities: CNNs are specifically designed for processing and analysing images. They excel at automatically learning and

extracting relevant features from visual data, making them well-suited for tasks like cancer cell detection. Since cancer cell detection involves analysing medical images, such as histopathological slides or radiological scans, CNNs are a natural choice.

2. Feature extraction: CNNs have the ability to capture intricate patterns and relationships within images. Cancer cells often exhibit distinctive characteristics, such as irregular shapes, abnormal textures, or specific structural properties. By training a CNN on a large dataset of cancer cell images, the model can learn to recognize and extract these features automatically, enabling accurate detection.
3. Hierarchical representation: CNNs employ multiple layers that progressively learn more abstract representations of the input data. This hierarchical representation is valuable in cancer cell detection because it allows the model to capture both local and global context. Different cancer cell types may have varying sizes, shapes, and orientations, and CNNs can effectively capture such complex information.