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Applied Artificial Intelligence

Assignment # 02

Artificial Neural Networks

Submitted To

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<u>Face Mask Detection via Deep Transfer Learning</u>

One possible solution for the detection of face masks from crowd source data is to use a deep learning-based approach that can locate and classify faces with or without masks in real-time. A deep learning model can be trained on a large and diverse dataset of images that contain faces with different types of masks, occlusions, angles, and lighting conditions. The model can then be deployed on edge devices, such as cameras or smartphones, to perform inference on the incoming video streams.

Following is the outline for implementing a solution using deep learning.

Data collection

1) **<u>Collection:</u>** Collecting data of people wearing and not wearing masks in different conditions low / high lighting, different angles, in blur, noise and so on.
2) **<u>Annotation:</u>** Annotating the data with face mask includes the determination of the coordinates where the person is wearing mask. This annotated data will help neural network learning the masked face and non-masked face.

Preprocessing

Preprocessing may include following steps:

1) Resizing images
2) Scaling annotations according to by determining the width and height ratio according to new size.
    a. width-ratio: new_size / original_width
    b. height-ratio: new_size / original_height
3) Normalizing the image pixels.

Data Augmentation

To increase the diversity of the data and improve class imbalance problems we can apply data augmentation for improving model generalization.

Model Development

1) **<u>Model Selection:</u>** Due to effectiveness of convolutional neural networks in image recognition tasks we can consider ResNet, MobileNet and EffectiveNet pre-trained models.
2) **<u>Training:</u>** Utilize the annotated dataset to train the model to recognize whether a person is wearing a mask or not. Transfer learning from pre-trained models can significantly aid in achieving better performance, especially when working with limited data.
3) **<u>Fine-tuning and Optimization</u>:** Experiment with hyperparameters, regularization techniques, and learning rates to enhance the model's accuracy and reduce overfitting.
4) **<u>Performance and Feeback:</u>** We can evaluate the performance of the model with respect to accuracy, F1 score, precision, and loss. And we can also test the model in different conditions of environment and see if the trained model can detect the mask and then incorporate the feedback accordingly.
5) **<u>Deployment:</u>** Finally, the fitted model can be deployed to the camera for real-time detection.

Report on Neural Networks for Cancer Detection and Classification

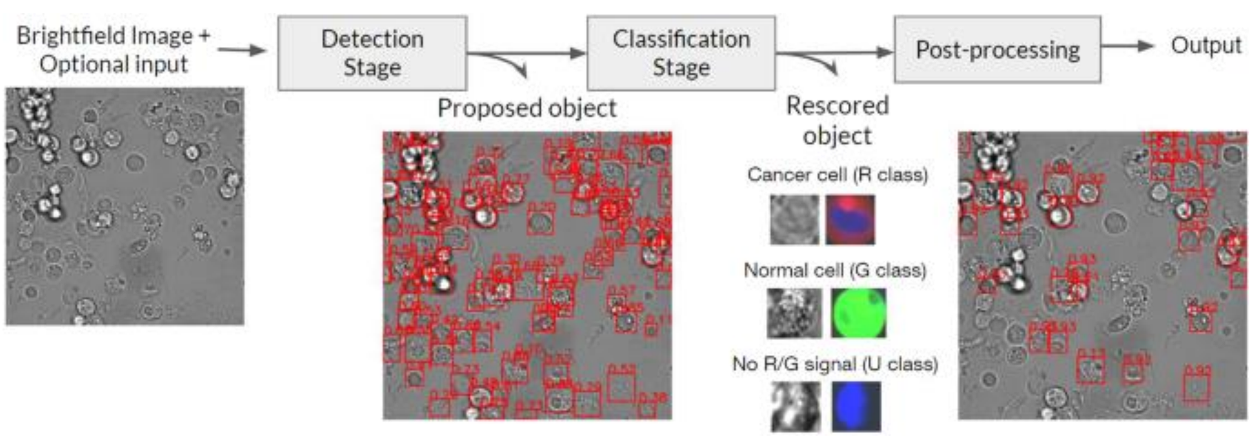
Introduction

Cancer remains a significant global health challenge, prompting extensive research into advanced technologies for early detection and accurate classification. Artificial Neural Networks (ANNs), a subset of machine learning algorithms inspired by the human brain's neural structure, have emerged as a promising tool in cancer detection and classification. This report aims to explore the application of ANNs in these critical areas of oncology.

ANNs in Cancer Detection

ANNs can be used to analyze and extract features from these data, and to learn patterns and relationships that can help distinguish between normal and cancerous cells, and between different types and subtypes of cancer. ANNs can also be used to predict the prognosis and response to treatment of cancer patients, based on their clinical and molecular characteristics.

For instance, in breast cancer detection, ANNs have demonstrated substantial success in distinguishing between benign and malignant tumors in mammographic images. By learning intricate patterns and features from images, ANNs can identify subtle abnormalities that might escape human observation, thereby aiding in early detection.



Advantages of using ANNs

Some of the advantages of using ANNs for cancer detection and classification are:

- ANNs can handle large and complex data, such as high-dimensional images and genomic data, and can learn from both labeled and unlabeled data.
- ANNs can capture nonlinear and complex relationships between the input and output variables and can generalize well to new and unseen data.
- ANNs can be integrated with other machine learning techniques, such as deep learning, reinforcement learning, and ensemble learning, to enhance their performance and robustness.

- ANNs can be customized and optimized for different types and domains of cancer and can be updated and retrained as new data and knowledge become available.

Classification of cancer cells via Deep Learning from Medical Images

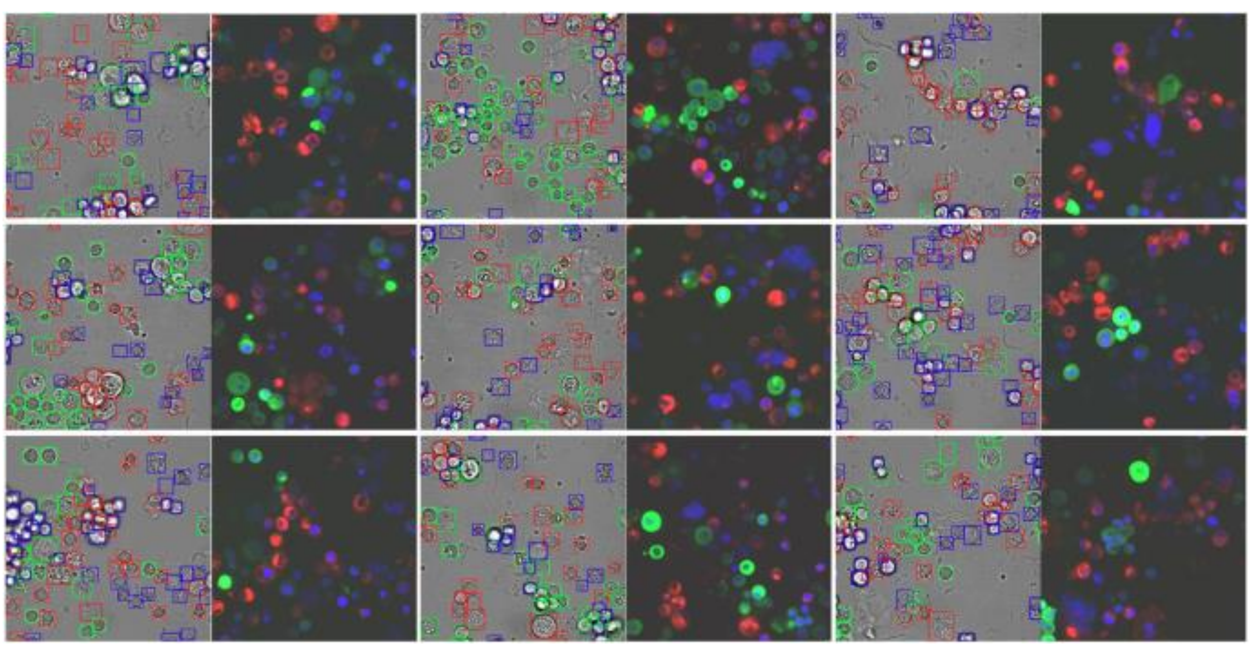
The following outline can be followed for the classification of cancer cells.

1) **<u>Data collection:</u>** We can gather comprehensive dataset of medical images which may be MRIs, CT scans and mammograms with annotations for supervised learning indicating the presence or absence of cancerous cells.

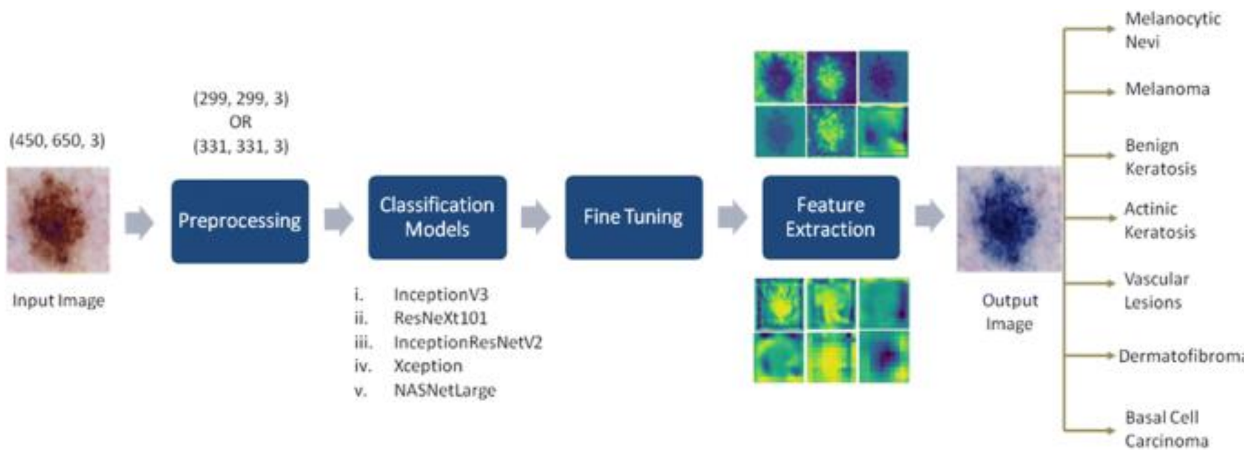
2) **<u>Preprocessing:</u>** We can preprocess the data, this may include
    a. Resizing images,
    b. Scaling annotations according to the new size to width / height ratio
    c. Normalizing the pixels
    d. Standardizing to ensure uniformity across the dataset.

3) **<u>Data Augmentation:</u>** If necessary, we may augment the dataset for increasing diversity and improving models' robustness and generalization.

4) **<u>Feature Extraction:</u>** Extract relevant features from the images. In medical imaging, these features might include texture, shape, intensity, and other characteristics that differentiate between healthy and cancerous tissues. For instance, in mammographic images, features like microcalcifications, masses, and architectural distortions could be important indicators of breast cancer.



5) **Model Selection:** We can employ Convolution Neural Networks due to their ability to learn hierarchical representations of image features. We may consider transfer learning by utilizing pre-trained CNN models (such as VGG, ResNet, MobileNet, or Inception) trained on large image datasets like ImageNet. We can Fine-tune these models on our medical imaging dataset to adapt them to cancer classification tasks.



6) **Training:** We can split the dataset into training, validation, and test sets. Use the training set to train the model, the validation set to tune hyperparameters, and the test set to evaluate the model's performance. Then training the model on the extracted features, optimizing it to accurately classify between cancerous and non-cancerous images.

7) **Model Evaluation and Validation:** Evaluate the model's performance using appropriate metrics like accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC). We can then validate the model's robustness by testing it on unseen data to ensure it generalizes well to new cases.

8) **Deployment and Clinical Integration:** Finally, implementing the trained model into clinical workflows or diagnostic systems to aid healthcare professionals in cancer diagnosis.

Conclusion

In conclusion, Artificial Neural Networks have shown immense potential in revolutionizing cancer detection and classification by leveraging complex data to aid in early diagnosis, prognosis, and personalized treatment strategies. Continued advancements in ANNs hold promise for further improving cancer management and patient outcomes.