SOMAIYA
VIDYAVIHAR UNIVERSITY
K J Somaiya College of Engineering

Detecting Gallbladder stones using Ultrasound images

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K J Somaiya College of Engineering

K. J. SOMAIYA COLLEGE OF ENGINEERING, VIDYAVIHAR, MUMBAI 400077
(A CONSTITUENT COLLEGE OF SOMAIYA VIDYAVIHAR UNIVERSITY)

Detecting Gallbladder stones using Ultrasound images

Branch: Computer Science

BY

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TOPICS COVERED

SCOPE

- The scope of this project encompasses the development and evaluation of a novel technique for improving the accuracy and effectiveness of gallbladder stone detection using ultrasound imaging (USG), with a specific focus on the detection of small stones.
- The project aims to provide a cost-effective alternative to the current standard practices, which often rely on expensive MRI and CT scans. The proposed technique involves two primary steps: gallbladder identification and region of interest (ROI) extraction, followed by the application of a second-order pooling architecture.
- Additionally, the project addresses the challenge of spurious texture in ultrasound images by drawing inspiration from human visual processes.
- The ultimate goal is to demonstrate that this innovative approach can surpass the performance of state-of-the-art convolutional neural networks (CNNs) in gallbladder stone detection.

PROBLEM STATEMENT

Challenge:

Need for Precision:

- Enhance accuracy in detecting gallbladder stones using USG.
- Current reliance on costly MRI and CT scans poses financial burdens.

Existing Practices:

MRI and CT Limitations:

- Standard practices heavily rely on costly MRI and CT scans.
- Financial strain on healthcare systems and patients due to high expenses.
- Limited accessibility to advanced diagnostic methods.

Objective:

- Affordable Innovation:
  - Propose a novel technique leveraging the affordability and accessibility of USG.
  - Aim to improve precision in gallbladder stone detection while reducing financial burdens.
  - Provide an alternative solution to the current reliance on expensive imaging methods.

Cost-Efficiency::

- Introduce a cost-effective solution that maintains diagnostic accuracy.
- Decrease dependence on expensive MRI and CT scans, making the procedure more accessible.

PROBLEM STATEMENT

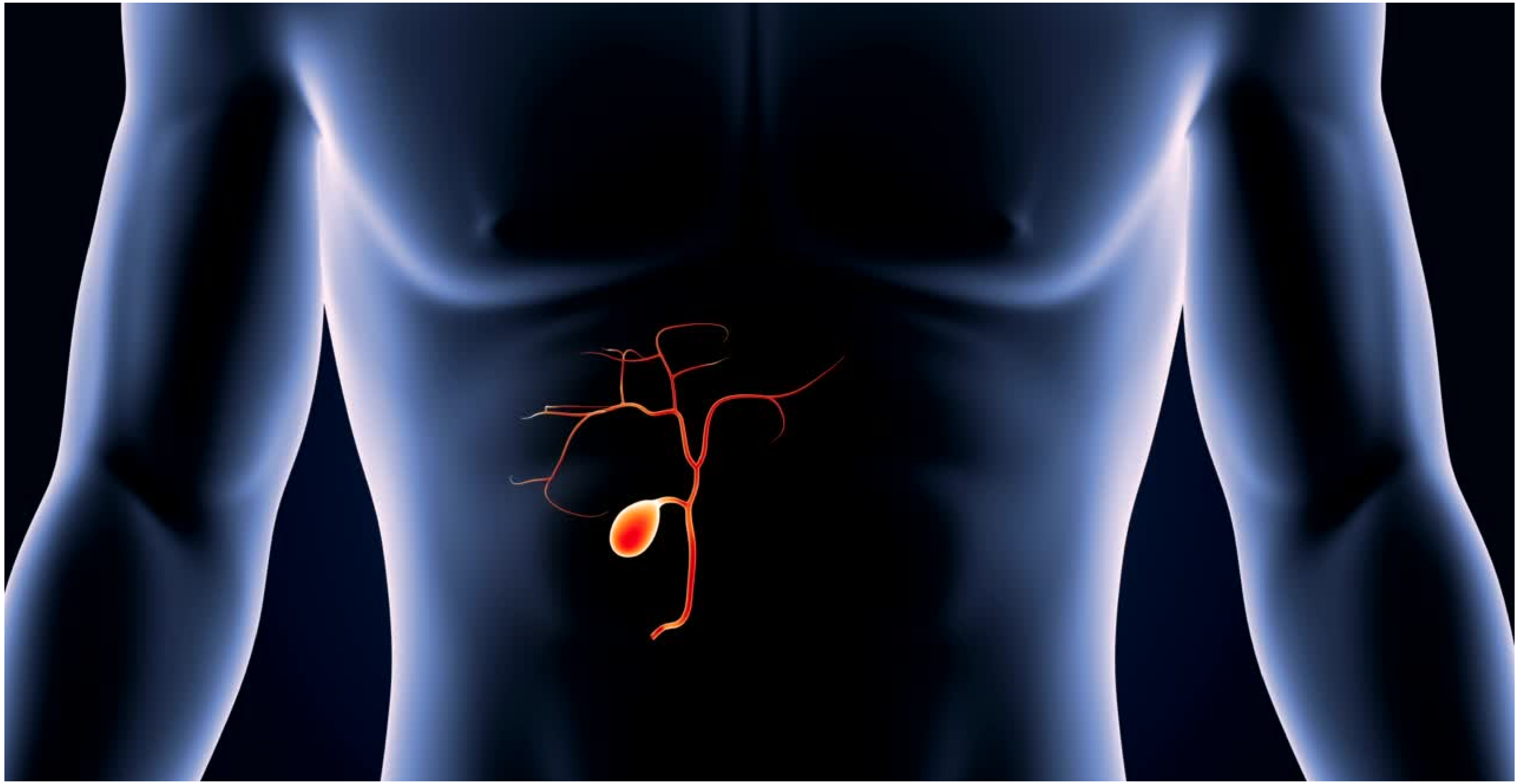
- The problem at hand revolves around the need to enhance the accuracy and effectiveness of gallbladder stone detection using ultrasound imaging (USG), particularly for the detection of small gallbladder stones. The existing standard practices for gallbladder stone diagnosis heavily rely on costly MRI and CT scans. These methods, while effective, pose financial burdens on healthcare systems and patients alike.

- Our primary objective is to propose and validate a novel technique that leverages the affordability and accessibility of USG to improve the precision of gallbladder stone detection. This innovative approach comprises two crucial steps:

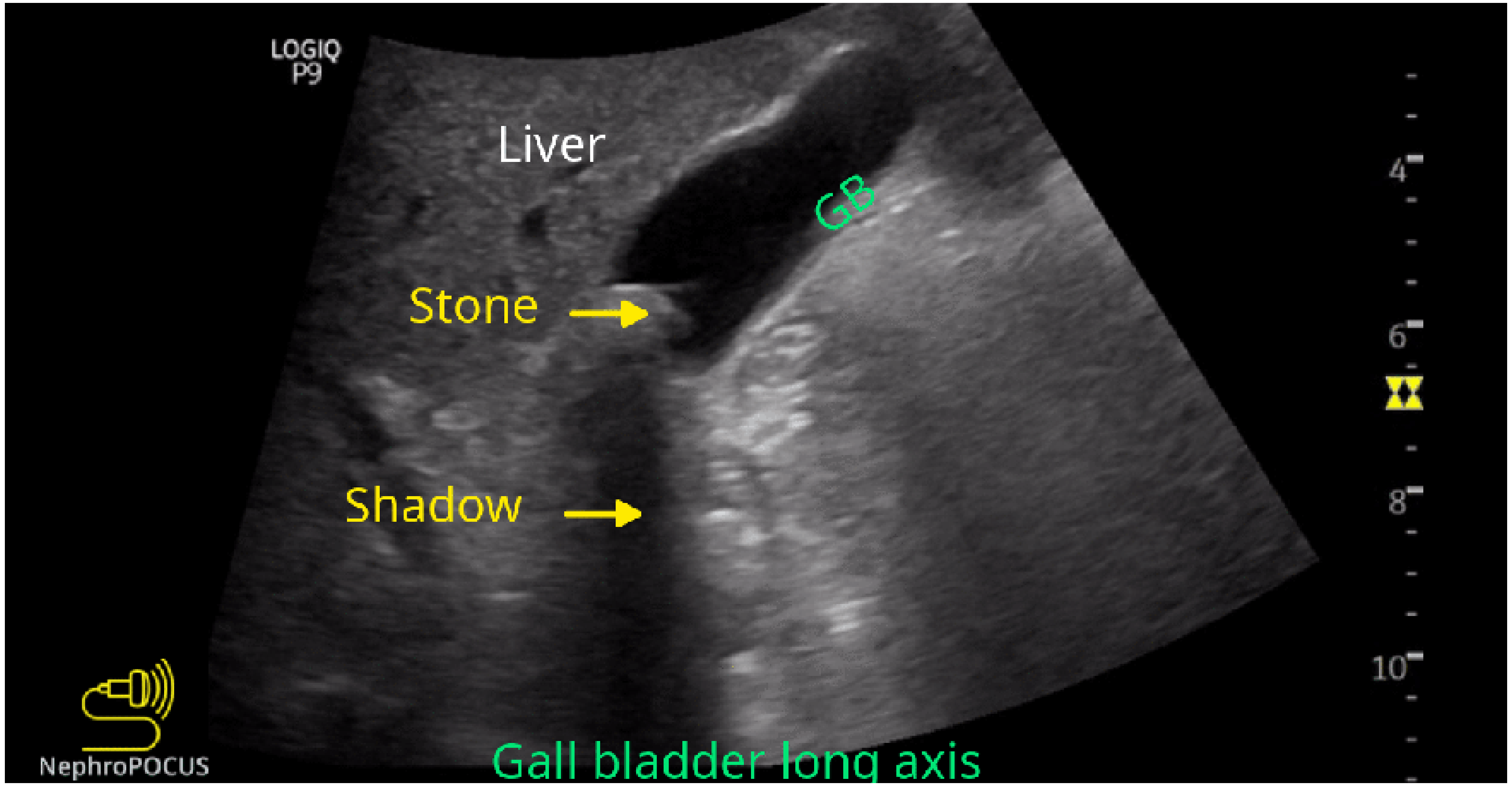
- Gallbladder Identification and ROI Extraction: The first step involves developing a robust algorithm to accurately identify the gallbladder within ultrasound images. Once the gallbladder is identified, the region of interest (ROI) containing potential gallbladder stones is extracted. This process must be efficient and reliable to ensure precise localization.

- Second-Order Pooling Architecture: In the second step, we implement a specialized second-order pooling architecture designed to analyze the ROIs for gallbladder stones. This architecture should be optimized to capture relevant features while minimizing noise and artifacts present in ultrasound images.

GALLBLADDER



GALLBLADDER



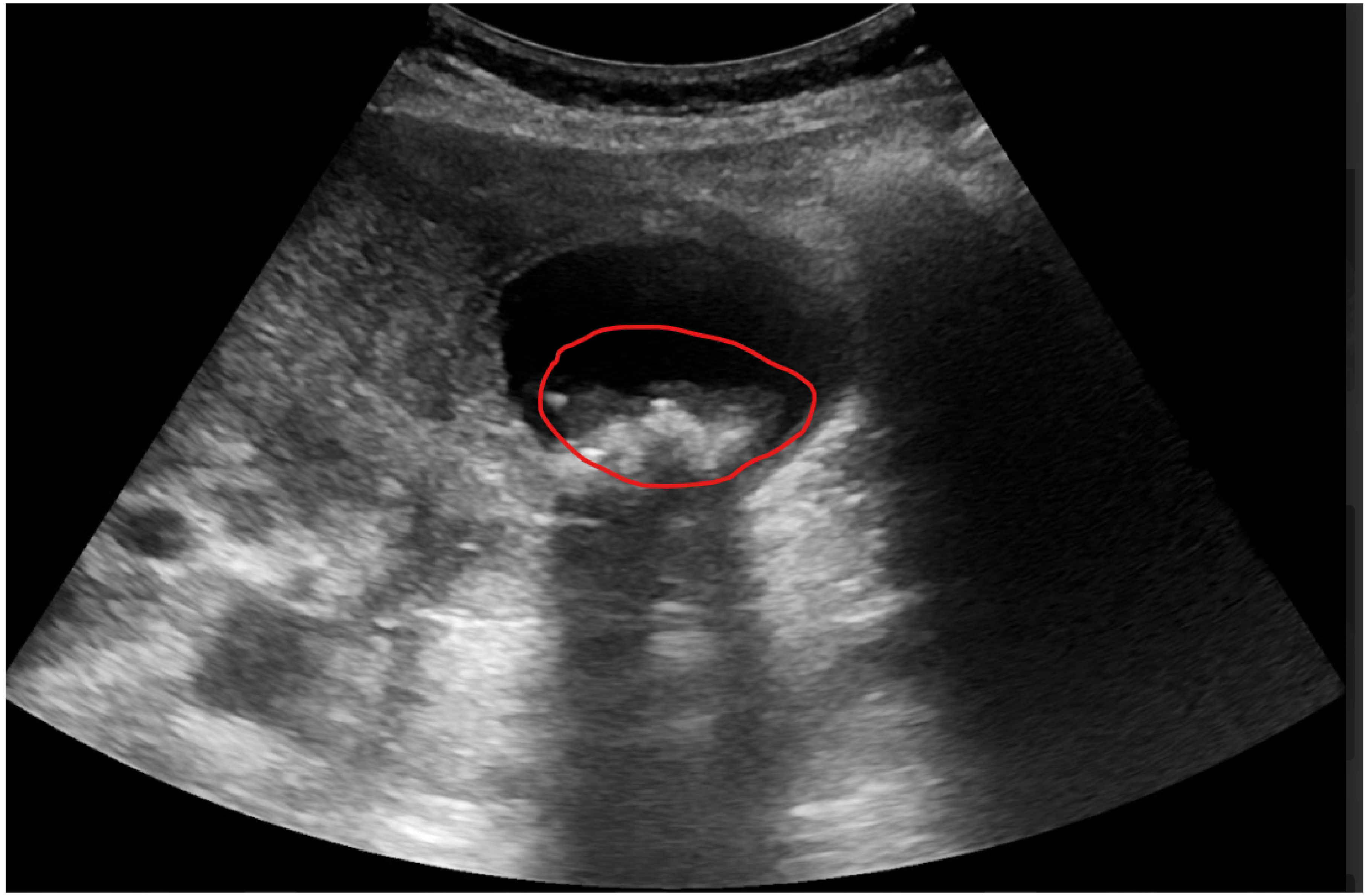
GALLBLADDER

Original Image

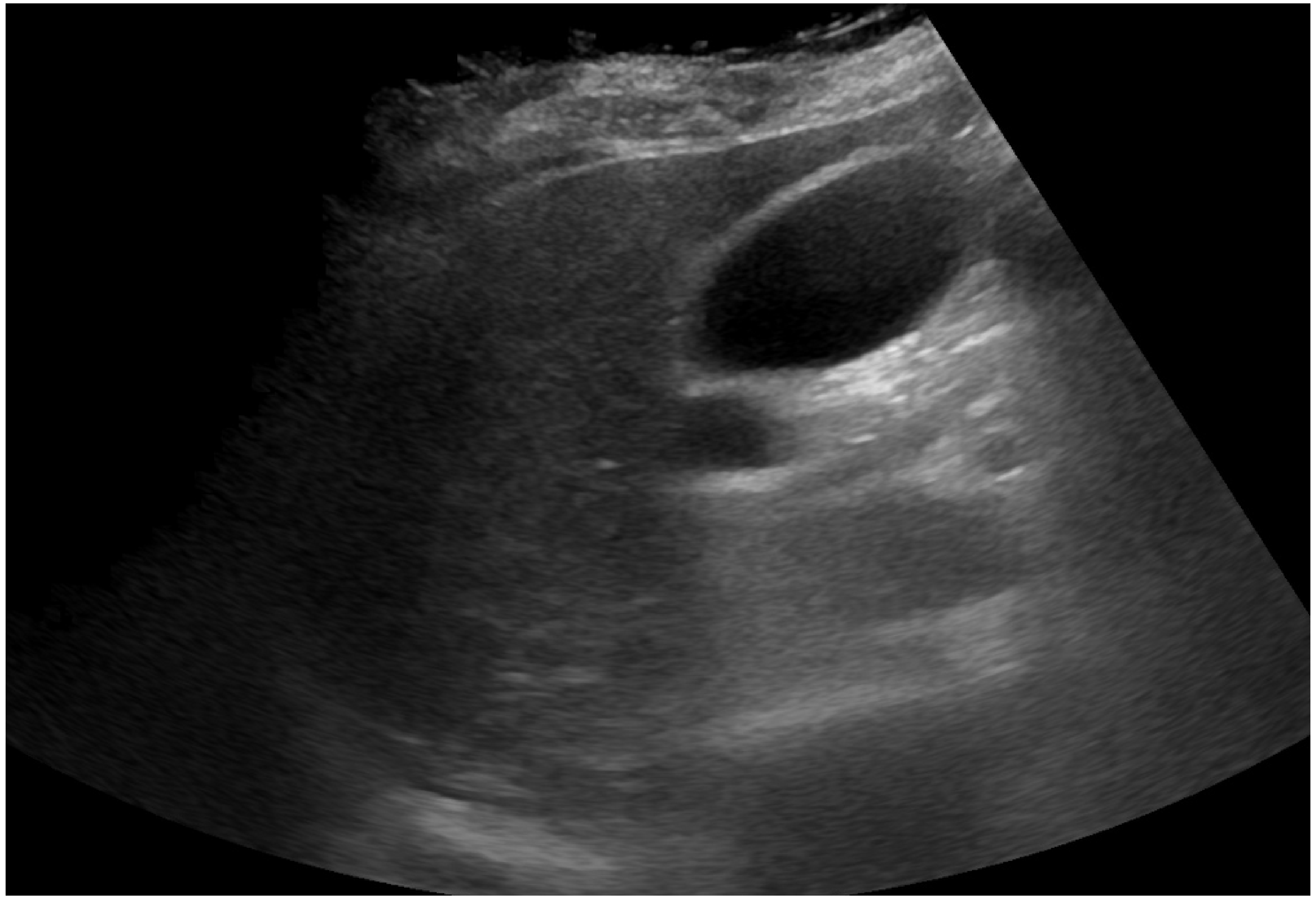
224 X 224

GALLBLADDER

WITH STONES



WITHOUT STONES



LITERATURE SURVEY

Gallbladder Cancer Detection:

- CNN-based models explored for gallbladder stones detection from USG images.
- Challenges include low image quality, noise, and varying viewpoints.
- Proposed RESNET-50 tackles shadows, spurious textures, outperforming SOTA models.

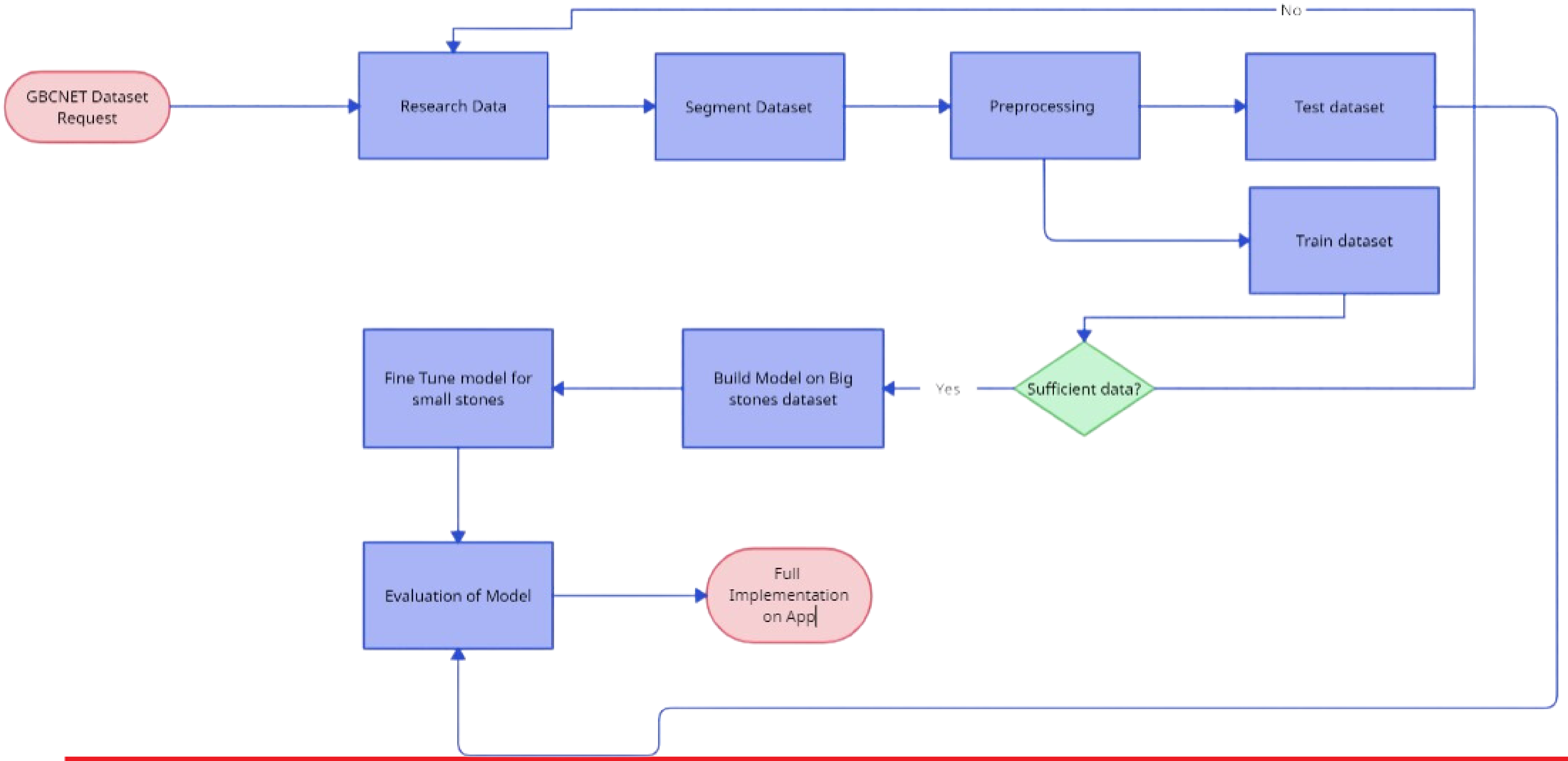
Curriculum learning :

- CNN models widely used for diagnosing gallbladder stones and related afflictions.
- Applications in USG imaging tasks for ovarian and breast cancer detection.
- Curriculum learning applied to improve various medical imaging tasks.

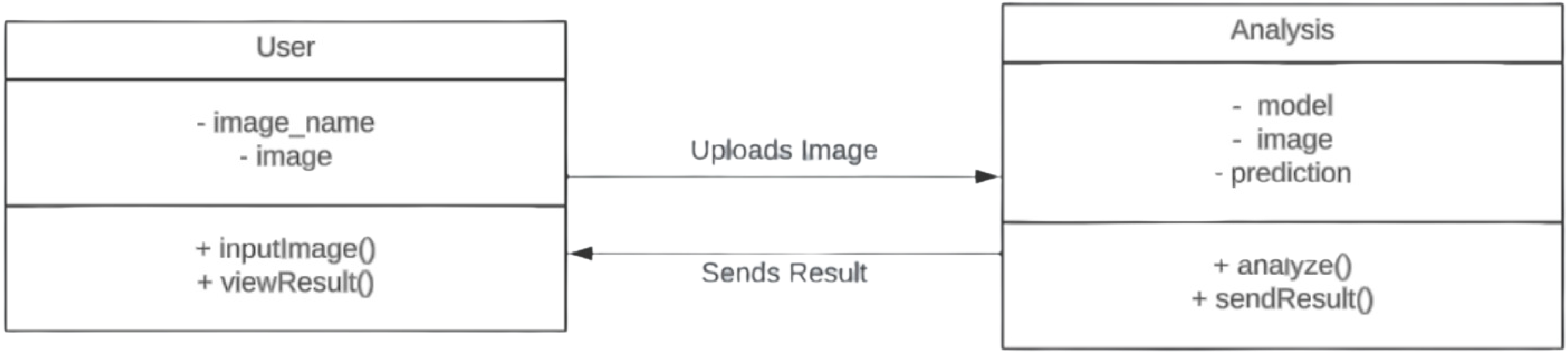
Very Deep Neural Networks:

- Concerns about texture bias in CNN architectures for USG imaging.
- RESNET-50 focuses on soft tissue textures; efforts to reduce bias and improve spatial understanding.

DATA FLOW DIAGRAM



CLASS DIAGRAM



Datasets

- **Gallbladder Cancer Ultrasound (GBCU) Dataset - https://gbc-iitd.github.io/data/gbcu**

We reached out to the owner of the dataset mentioned in the research paper and formally requested access to the dataset to augment the robustness of our project.

Datasets

- So in summary, this dataset contains ~1200 ultrasound images of the gallbladder with labels.
- Being raw ultrasound scans, The dataset exhibits certain challenges related to image quality, specifically characterized by the presence of noise and motion blur.
- The dataset comprises two categories—images featuring gallbladder stones and those without.
- Each image is finely detailed at a resolution of 1246 x 243 pixels, ensuring clarity in visual representation.
- All images are formatted in JPEG, offering a standardized and widely compatible structure for our project's analysis.

Datasets

- In our journey towards creating an effective gallbladder stone detection model, we initially grappled with a disorganized and unlabeled dataset. Rigorous efforts were dedicated to labeling and organizing the data, laying the foundation for subsequent steps.

- To enhance model accuracy, we explored the application of Gaussian filters. However, faced with limited success, we adopted a streamlined approach—resizing the images. This decision not only standardized the dataset but also prioritized computational efficiency during training.

- Our focus on simplicity and efficiency aligns with our goal of developing an accurate gallbladder stone detection model. This adaptive preprocessing strategy serves as a pivotal step in optimizing both dataset structure and model training efficiency.

H/W and S/W requirement

Hardware Requirements:

1. **Computer System:**
    - Processor: Quad-core or higher CPU.
    - RAM: 8 GB or more.
    - Storage: Solid State Drive (SSD) for faster data access.
    - GPU (Graphics Processing Unit): A capable GPU, optional but highly recommended for accelerated deep learning tasks.

Software Requirements:

1. **Operating System:**
    - A 64-bit operating system is recommended.
    - Options: Windows 10 or later, Linux distributions (e.g., Ubuntu, CentOS), macOS (for development purposes).
2. **Development Environment:**
    - Python (preferred language).
    - Google Colab
    - Jupyter Notebook or integrated development environments (IDEs) like PyCharm or Visual Studio Code.
3. **Deep Learning Frameworks:**
    - TensorFlow.
    - PyTorch.

Additional Libraries and Packages:

- Various Python libraries and packages for image processing, data manipulation, and visualization, including but not limited to:
    - OpenCV
    - NumPy
    - Matplotlib
    - Scikit-learn
    - Pandas

1. **Database Management System (Optional):**
    - To accelerate deep learning model training, a compatible NVIDIA GPU and appropriate GPU drivers may be required, along with libraries such as CUDA and cuDNN.
2. **Cloud Services (Optional):**
    - Version control systems like Git, and platforms like GitHub or GitLab may be used for code version management and collaboration.

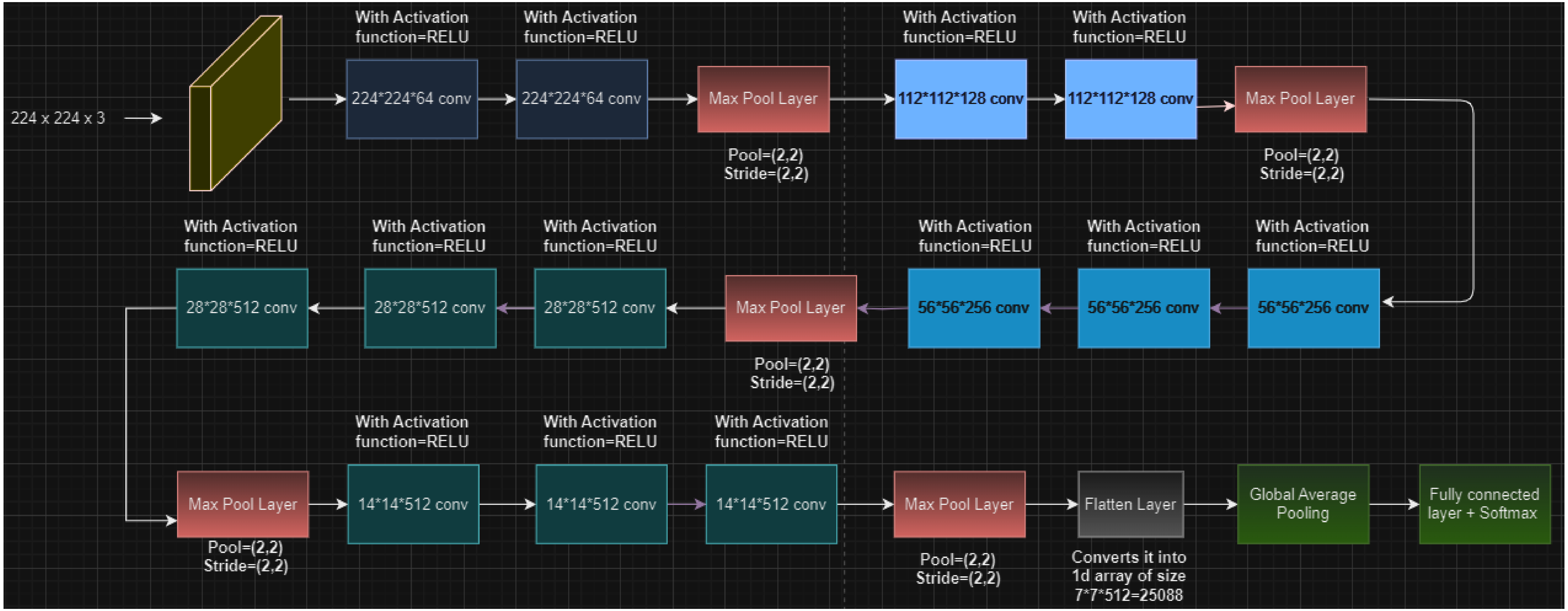
ADVANTAGES OF SELECTED MODELS FOR GALLBLADDER STONE DETECTION

1. **VGG-16:**
   - **Simple and Robust:** VGG-16 has a straightforward architecture with a uniform structure, making it easy to understand and implement.
   - **Effective Feature Extraction:** VGG-16 is known for its ability to capture intricate features, which can be crucial for distinguishing subtle patterns in medical images.
2. **ResNet-50:**
   - **Residual Learning:** The introduction of residual connections in ResNet-50 helps overcome the challenges of training very deep networks by mitigating the vanishing gradient problem.
   - **Better Training Performance:** ResNet-50's architecture allows for the training of deeper models, potentially enhancing the model's ability to learn complex features relevant to gallbladder stone detection.
3. **MobileNetV2:**
   - **Lightweight and Efficient:** MobileNetV2 is designed for mobile and edge devices, making it suitable for applications with resource constraints.
   - **Fast Inference:** MobileNetV2 excels in terms of computational efficiency, which can be beneficial for real-time or resource-constrained scenarios, ensuring quick and efficient gallbladder stone detection.

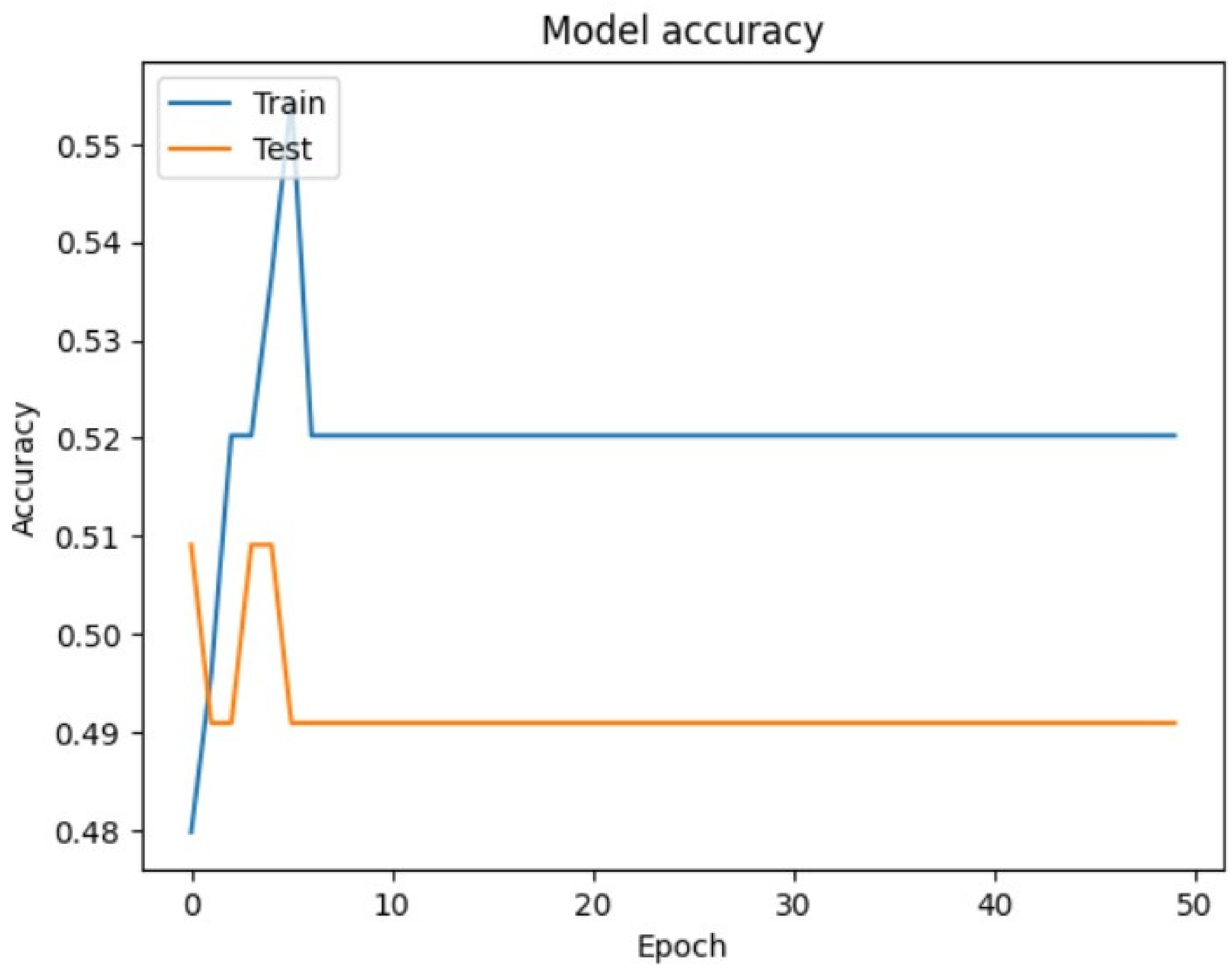
VGG-16

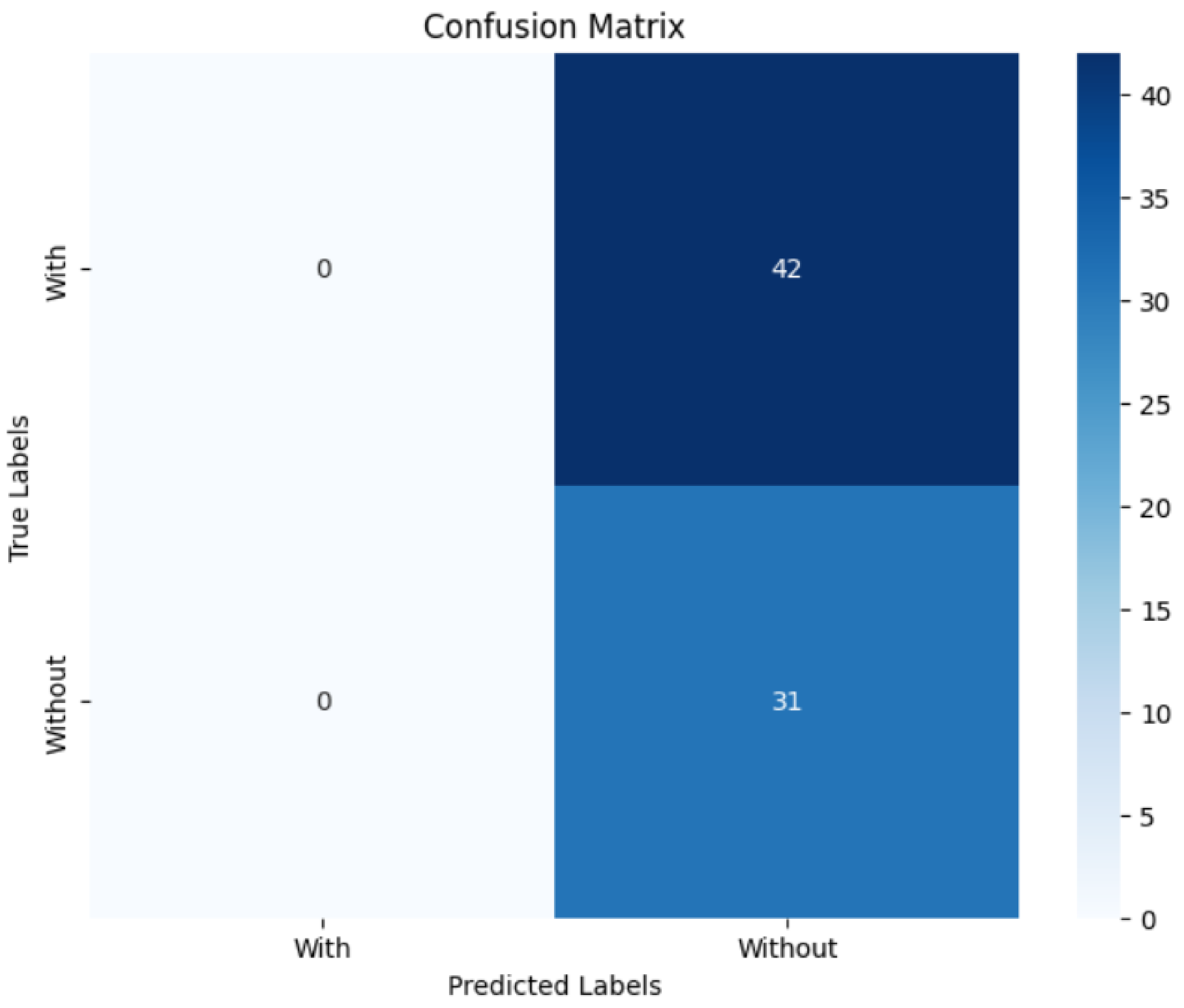
- **Deep Structure for Complexity:** VGG-16 boasts a deep architecture with 16 layers, including 13 convolutional and three fully connected layers. This depth allows the network to learn intricate hierarchical representations, proving effective for tasks like object recognition.
- **Pattern Recognition Prowess:** VGG-16 excels at recognizing patterns and features in images. Its capability to extract both low-level details and high-level features makes it a reliable choice for image classification.
- **Simplicity with Impact:** Despite its simple design, VGG-16 stands out as a robust and influential convolutional neural network in computer vision. Widely adopted, it showcases enduring effectiveness in various applications, emphasizing its impact in the field.

VGG-16


224 x 224 x 3
With Activation function=RELU
224*224*64 conv
With Activation function=RELU
224*224*64 conv
Max Pool Layer
Pool=(2,2) Stride=(2,2)
With Activation function=RELU
112*112*128 conv
With Activation function=RELU
112*112*128 conv
Max Pool Layer
Pool=(2,2) Stride=(2,2)
With Activation function=RELU
56*56*256 conv
With Activation function=RELU
56*56*256 conv
With Activation function=RELU
56*56*256 conv
Max Pool Layer
Pool=(2,2) Stride=(2,2)
With Activation function=RELU
28*28*512 conv
With Activation function=RELU
28*28*512 conv
With Activation function=RELU
28*28*512 conv
Max Pool Layer
Pool=(2,2) Stride=(2,2)
With Activation function=RELU
14*14*512 conv
With Activation function=RELU
14*14*512 conv
With Activation function=RELU
14*14*512 conv
Max Pool Layer
Pool=(2,2) Stride=(2,2)
Flatten Layer
Converts it into 1d array of size 7*7*512=25088
Global Average Pooling
Fully connected layer + Softmax

VGG-16

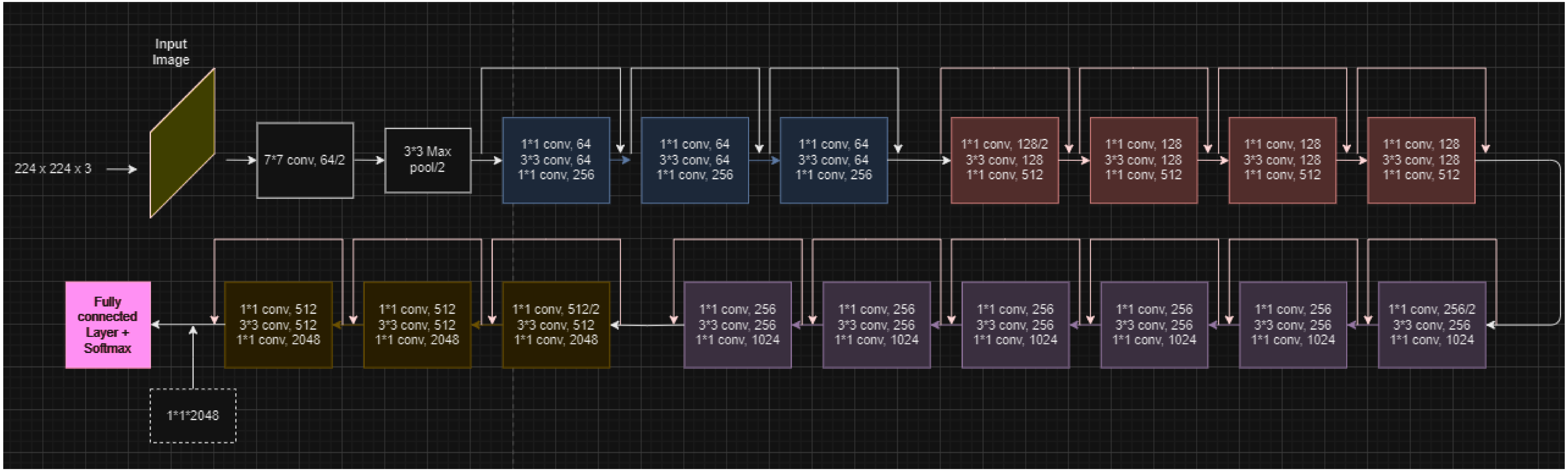

Model accuracy
Train
Test
Accuracy
0.55
0.54
0.53
0.52
0.51
0.50
0.49
0.48
0
10
20
30
40
50
Epoch


Confusion Matrix
True Labels
With
Without
0
42
0
31
With
Without
Predicted Labels
40
35
30
25
20
15
10
5
0

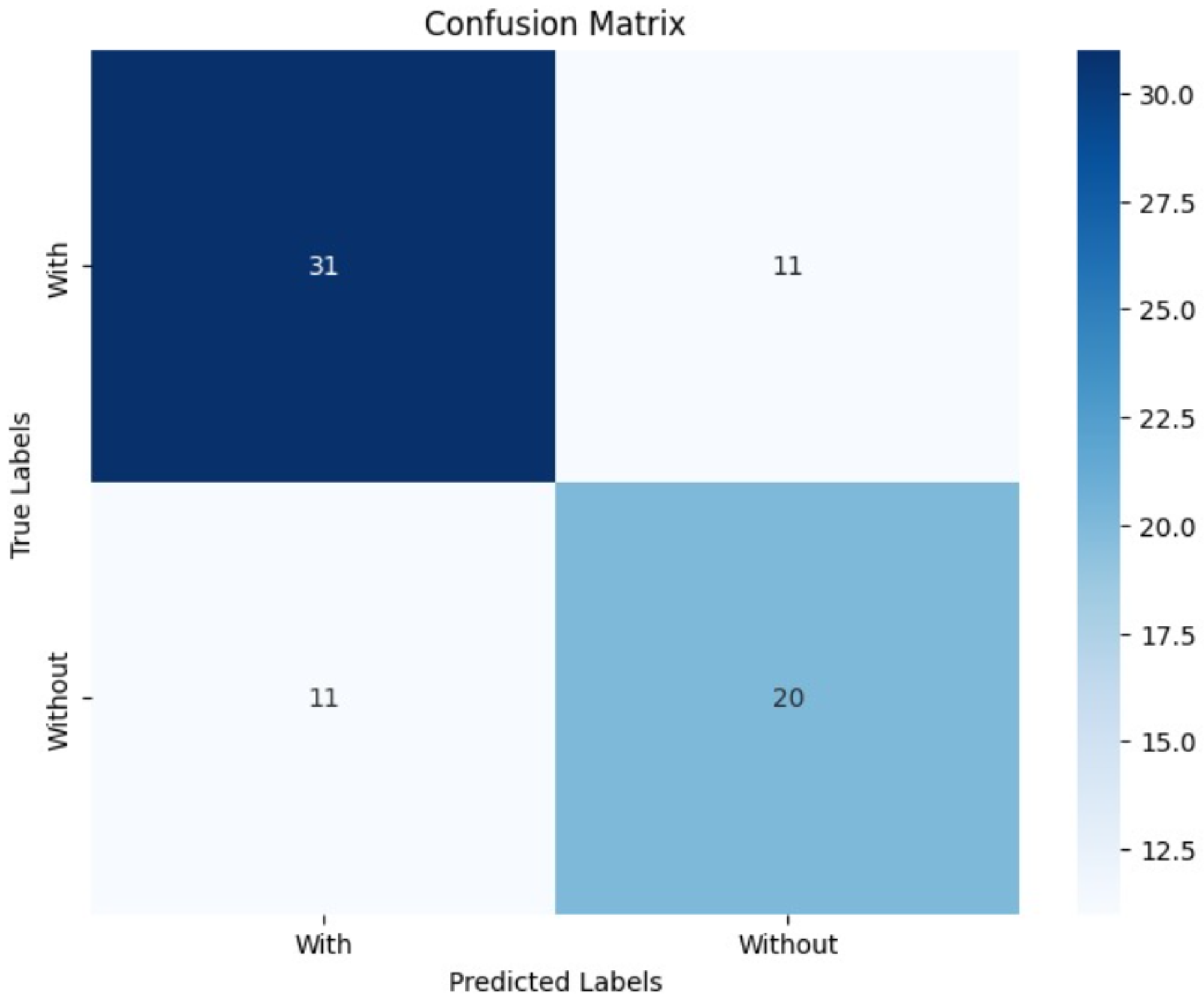
RESNET-50

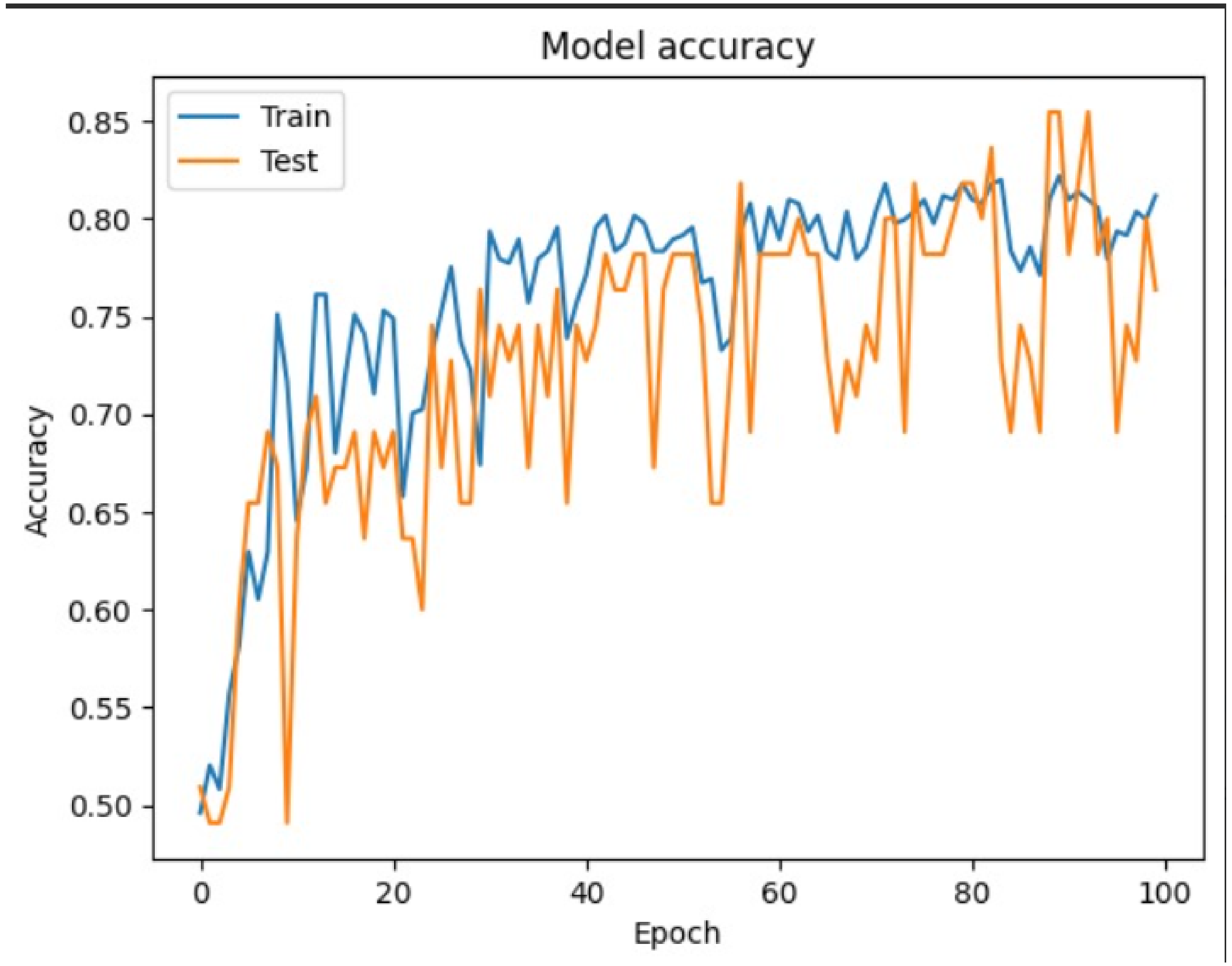
- **Deep Learning Powerhouse:** ResNet-50, standing for Residual Network with 50 layers, is a robust deep learning architecture crafted to tackle the complexities of training very deep neural networks.
- **Intricate Feature Capture:** ResNet-50 excels in capturing intricate features, particularly in tasks like image recognition. The integration of skip connections ensures a smoother and more efficient flow of information, enabling the successful training of exceptionally deep models.
- **Versatile in Computer Vision:** ResNet-50 is widely favored in computer vision applications due to its innovative design. The inclusion of skip connections enhances its ability to handle complex visual tasks, showcasing improved training efficiency and overall performance.

RESNET-50


Input Image
224 x 224 x 3
7*7 conv, 64/2
3*3 Max pool/2
1*1 conv, 64
3*3 conv, 64
1*1 conv, 256
1*1 conv, 64
3*3 conv, 64
1*1 conv, 256
1*1 conv, 64
3*3 conv, 64
1*1 conv, 256
1*1 conv, 128/2
3*3 conv, 128
1*1 conv, 512
1*1 conv, 128
3*3 conv, 128
1*1 conv, 512
1*1 conv, 128
3*3 conv, 128
1*1 conv, 512
1*1 conv, 128
3*3 conv, 128
1*1 conv, 512
1*1 conv, 256/2
3*3 conv, 256
1*1 conv, 1024
1*1 conv, 256
3*3 conv, 256
1*1 conv, 1024
1*1 conv, 256
3*3 conv, 256
1*1 conv, 1024
1*1 conv, 256
3*3 conv, 256
1*1 conv, 1024
1*1 conv, 256
3*3 conv, 256
1*1 conv, 1024
1*1 conv, 256
3*3 conv, 256
1*1 conv, 1024
1*1 conv, 512/2
3*3 conv, 512
1*1 conv, 2048
1*1 conv, 512
3*3 conv, 512
1*1 conv, 2048
1*1 conv, 512
3*3 conv, 512
1*1 conv, 2048
Fully connected Layer + Softmax
1*1*2048

RESNET-50


Confusion Matrix
31
11
11
20
With
Without
True Labels
With
Without
Predicted Labels
30.0
27.5
25.0
22.5
20.0
17.5
15.0
12.5


Model accuracy
Train
Test
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
Accuracy
0
20
40
60
80
100
Epoch

RESNET-50

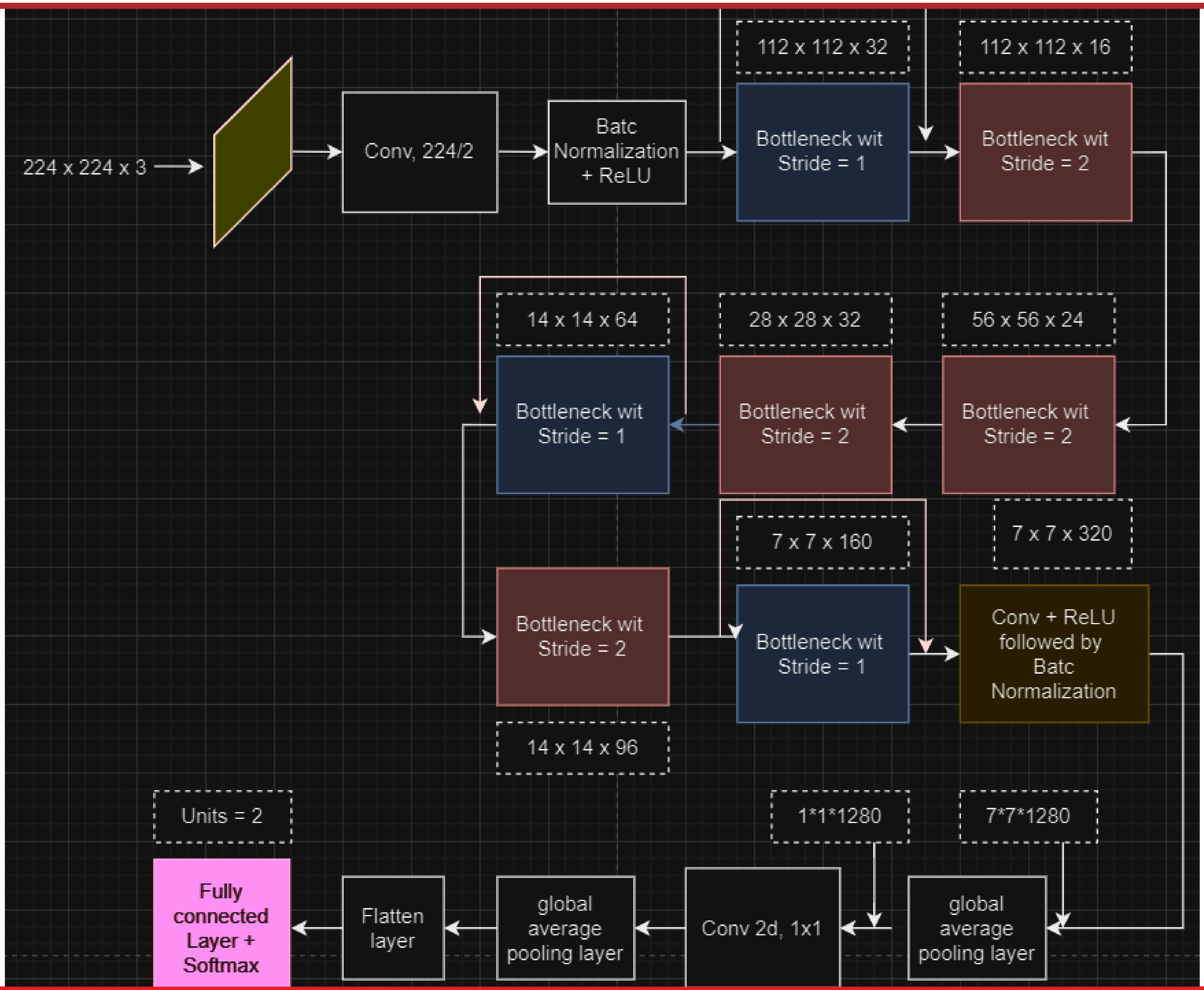
```
from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score

PrecisionScore = TP / (FP + TP)
print('Precision: %.3f' % precision_score(true_labels,predicted_labels))
RecallScore = TP / (FN + TP)
print('Recall: %.3f' % recall_score(true_labels,predicted_labels))
AccuracyScore = (TP + TN)/ (TP + FN + TN + FP)
print('Accuracy: %.3f' % accuracy_score(true_labels,predicted_labels))
F1Score = 2 * PrecisionScore * RecallScore / (PrecisionScore + RecallScore)
print('F1 Score: %.3f' % f1_score(true_labels,predicted_labels))
```

```
Precision: 0.645
Recall: 0.645
Accuracy: 0.699
F1 Score: 0.645
```

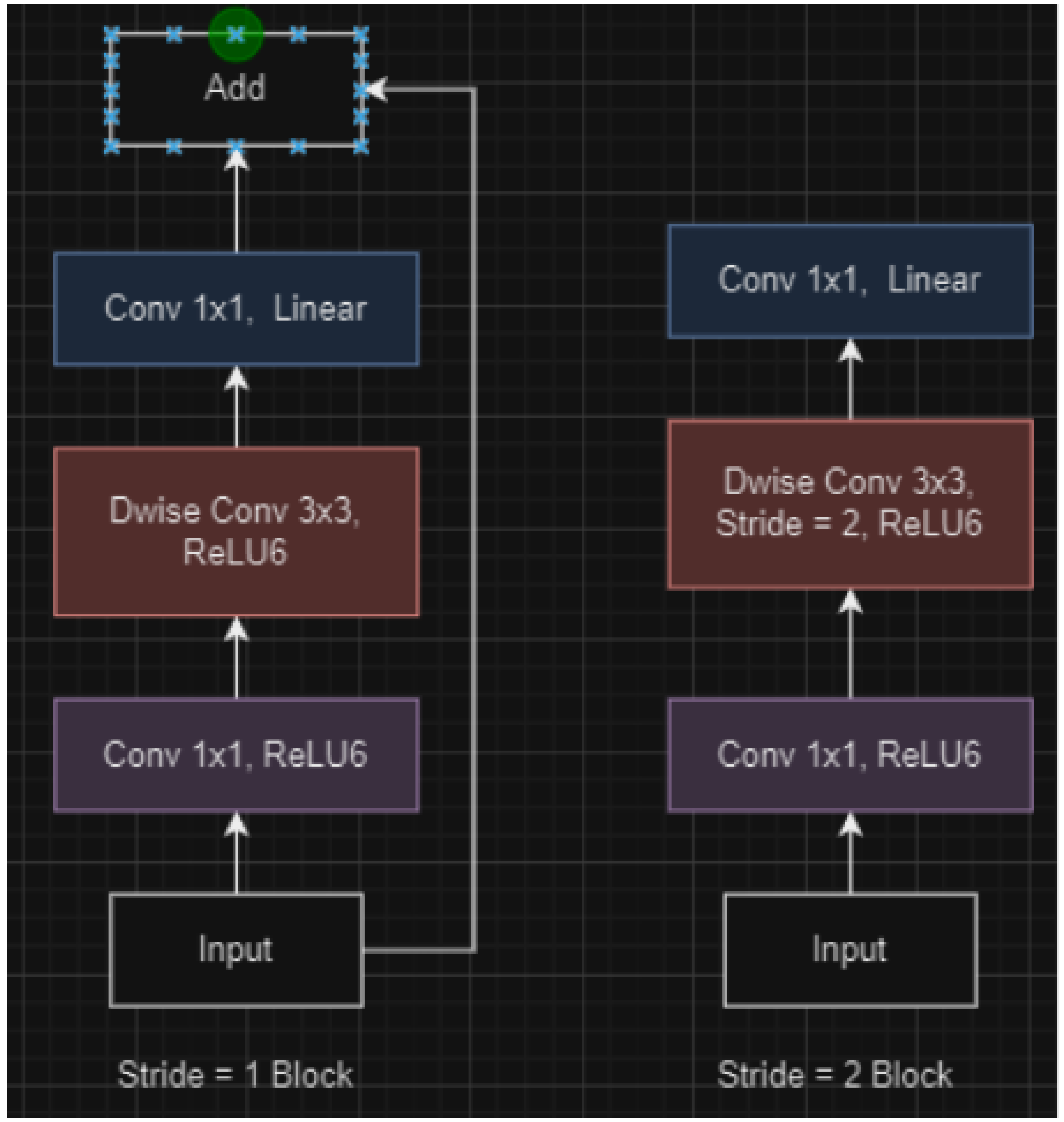
MOBILENETV2

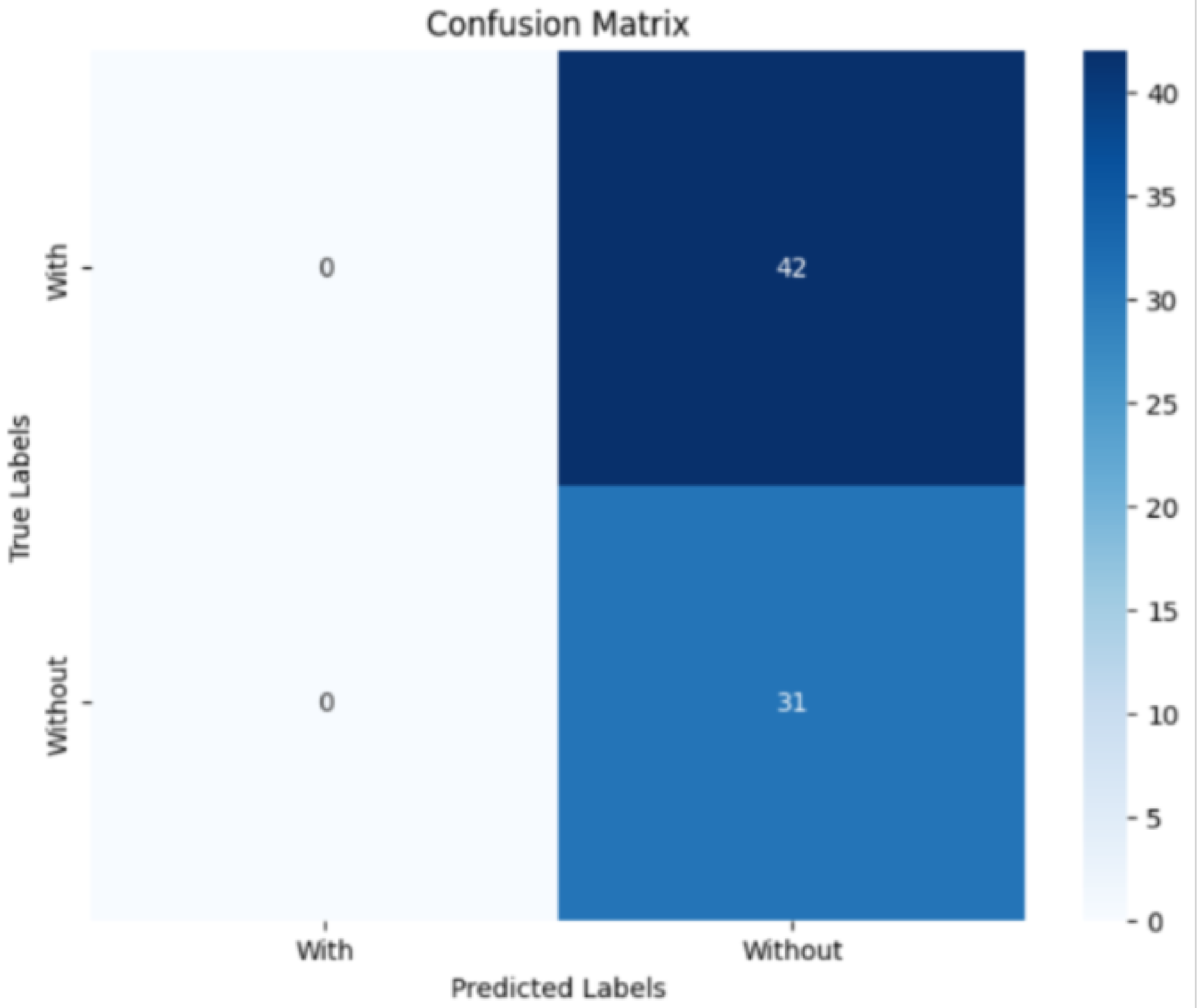
- **Efficient Mobile Architecture:** MobileNetV2 is a breakthrough in mobile-oriented deep learning, known for its lightweight design and superior performance.
- **Optimal Efficiency and Accuracy:** Leveraging inverted residuals and linear bottlenecks, MobileNetV2 strikes a balance between model efficiency and accuracy, making it ideal for devices with constrained computational resources.
- **Flexibility in Vision Tasks:** With innovative design elements, MobileNetV2 excels in computer vision. Its ability to adjust width multipliers and input resolutions ensures improved inference speed without compromising predictive capabilities.

MOBILENETV2



MOBILENETV2

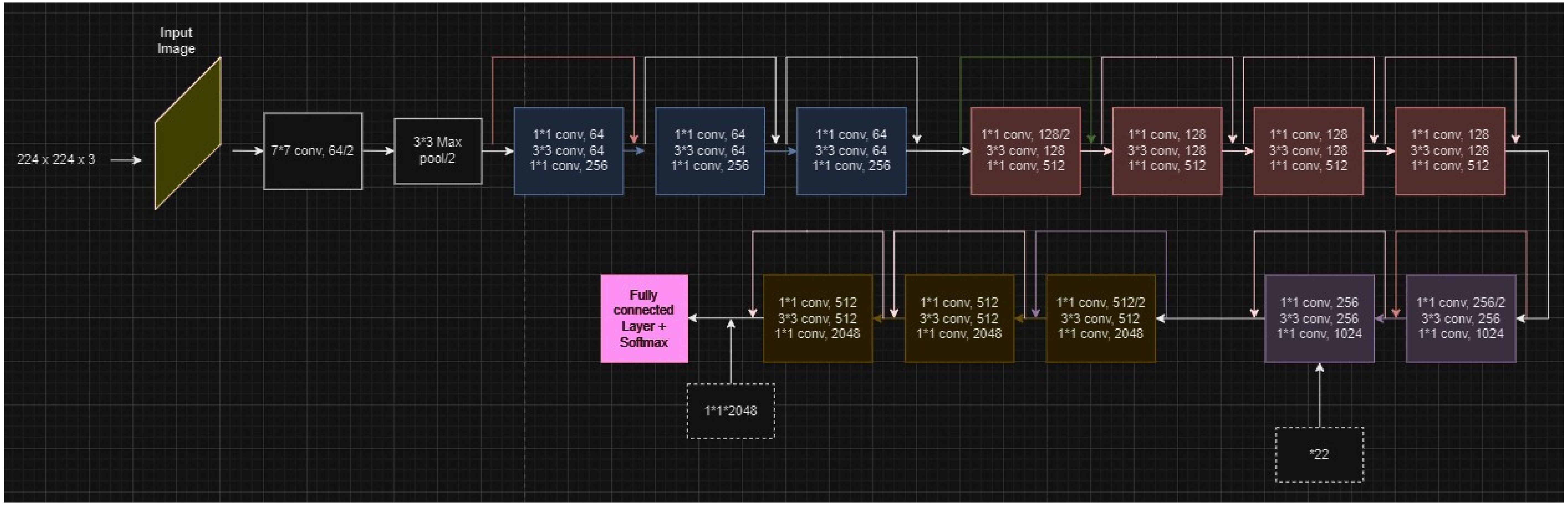




RESNET-101

- **Deep Residual Learning:** ResNet-101 is a deep neural network featuring 101 layers and introduces residual learning. Its unique skip connections enable the direct flow of information between layers, addressing challenges in training very deep networks.
- **Identity Mapping for Gradient Flow:** ResNet-101 uses identity mapping with skip connections to maintain a smooth gradient flow during training. This allows the model to effectively learn both low-level and high-level features, enhancing performance in tasks like image recognition.
- **Versatile High-Performance Architecture:** ResNet-101 excels in various computer vision tasks, offering exceptional performance and robustness. Its 101 layers enable the capture of intricate features, making it a widely adopted choice in both research and practical applications

RESNET-101


Input Image
224 x 224 x 3
7*7 conv, 64/2
3*3 Max pool/2
1*1 conv, 64
3*3 conv, 64
1*1 conv, 256
1*1 conv, 64
3*3 conv, 64
1*1 conv, 256
1*1 conv, 64
3*3 conv, 64
1*1 conv, 256
1*1 conv, 128/2
3*3 conv, 128
1*1 conv, 512
1*1 conv, 128
3*3 conv, 128
1*1 conv, 512
1*1 conv, 128
3*3 conv, 128
1*1 conv, 512
1*1 conv, 128
3*3 conv, 128
1*1 conv, 512
1*1 conv, 256/2
3*3 conv, 256
1*1 conv, 1024
1*1 conv, 256
3*3 conv, 256
1*1 conv, 1024
*22
1*1 conv, 512/2
3*3 conv, 512
1*1 conv, 2048
1*1 conv, 512
3*3 conv, 512
1*1 conv, 2048
1*1 conv, 512
3*3 conv, 512
1*1 conv, 2048
1*1*2048
Fully connected Layer + Softmax

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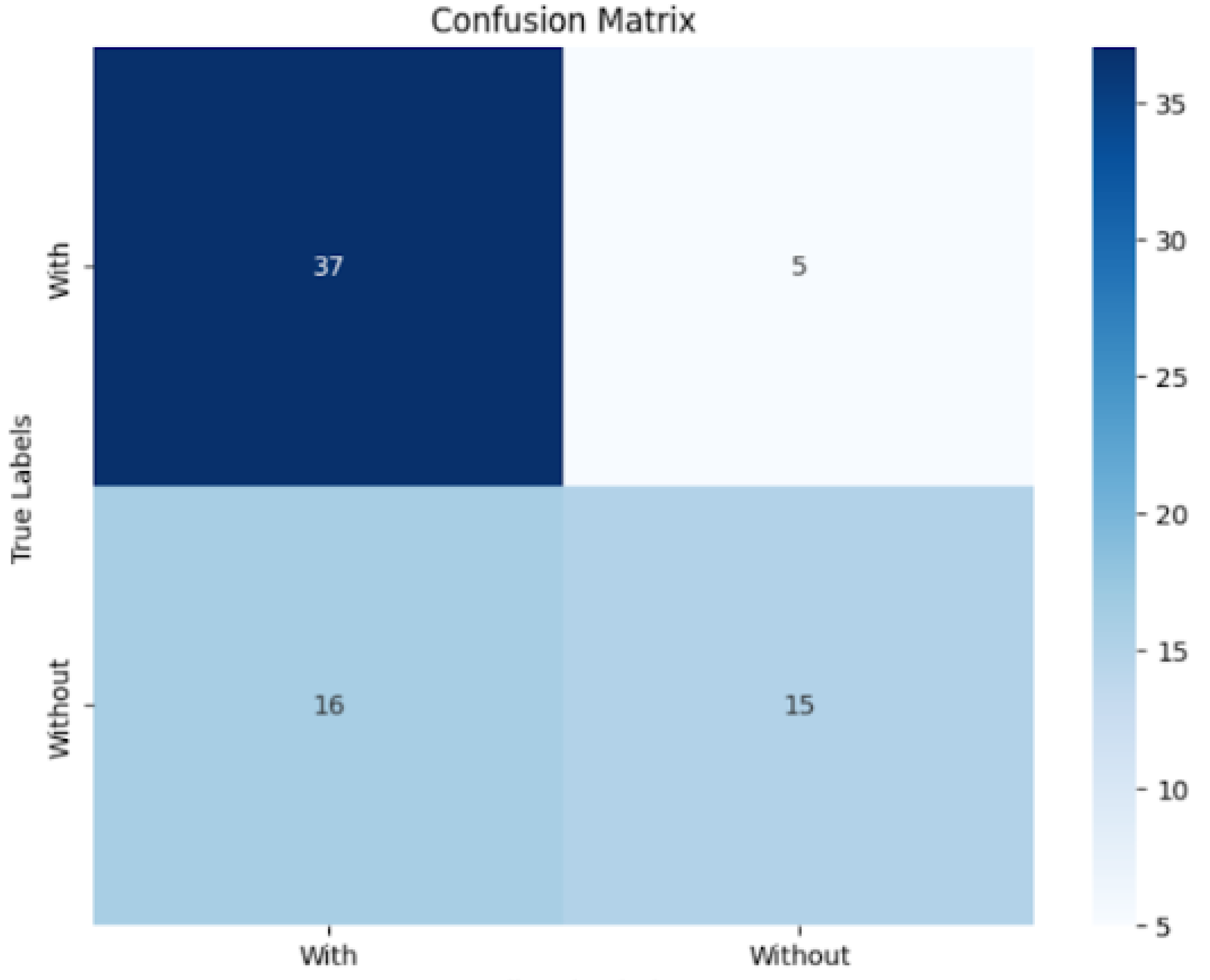
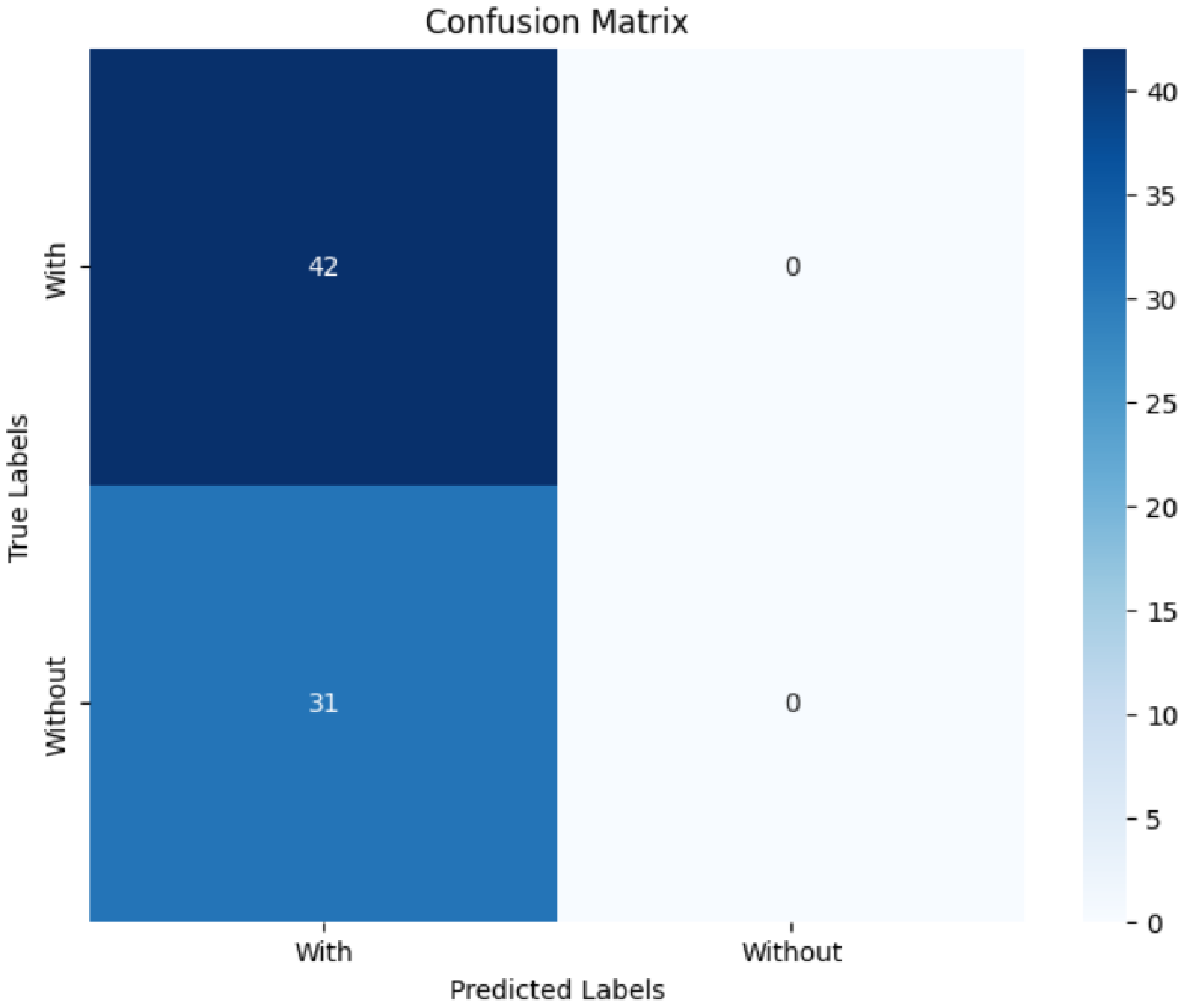
RESNET-101



DENSENET



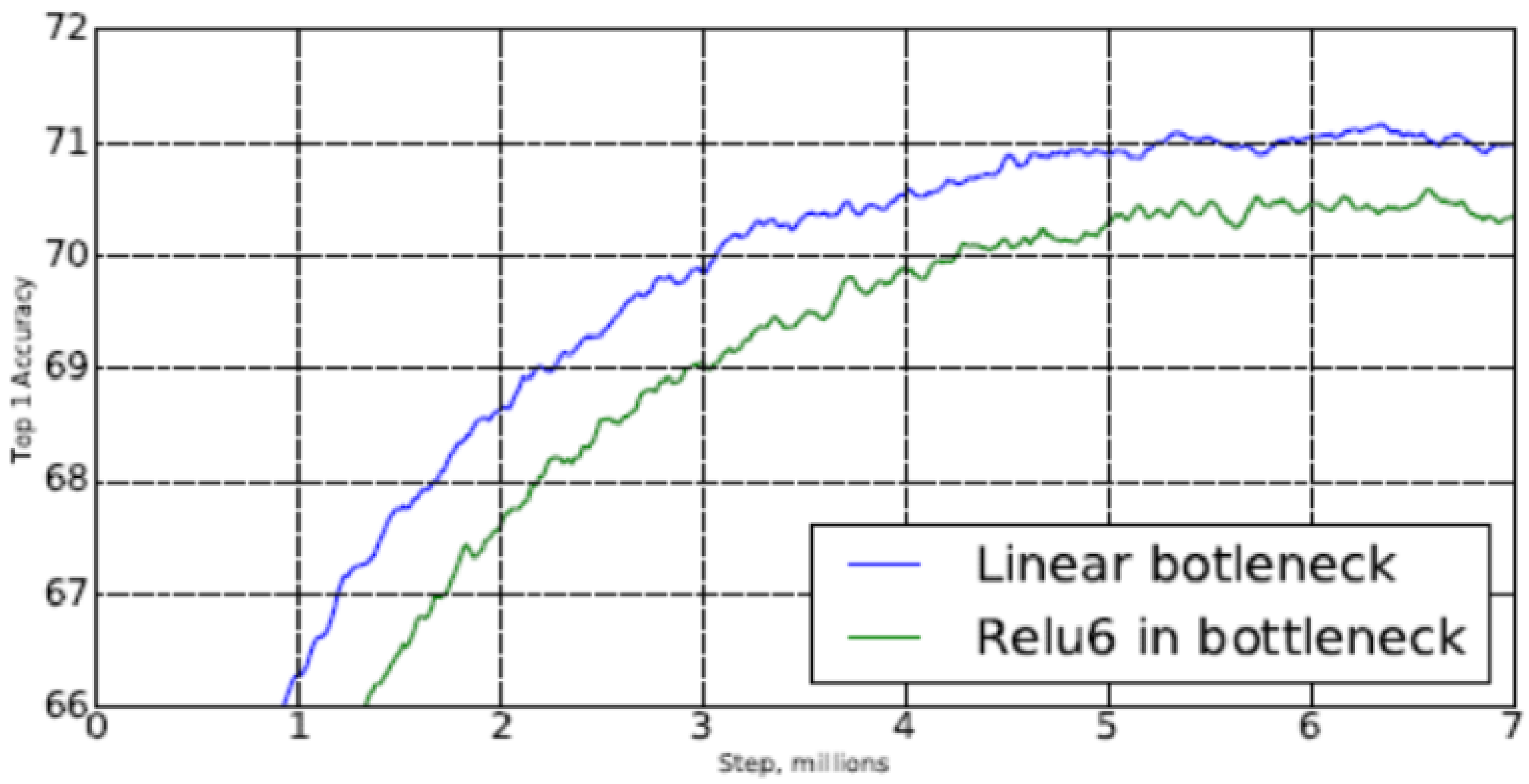
- **Dense Connectivity:** DenseNet employs dense connections, ensuring each layer receives direct input from all preceding layers, fostering efficient feature reuse and information flow.
- **Compact Feature Concatenation:** Feature maps from different layers are concatenated, reducing redundancy and promoting parameter efficiency, leading to more compact models.
- **Effective Regularization:** With batch normalization and feature concatenation, DenseNet acts as an effective regularizer, mitigating overfitting and enhancing training stability for improved performance.

COMPARISON OF ALL MODELS

	VGG- 16	RESNET-50	RESNET-101	MOBILENETV2
PRECISION	0	0.738	0.750	0
ACCURACY	0	0.698	0.712	0
RECALL	0	0.738	0.484	0
F1 score	0	0.738	0.588	0

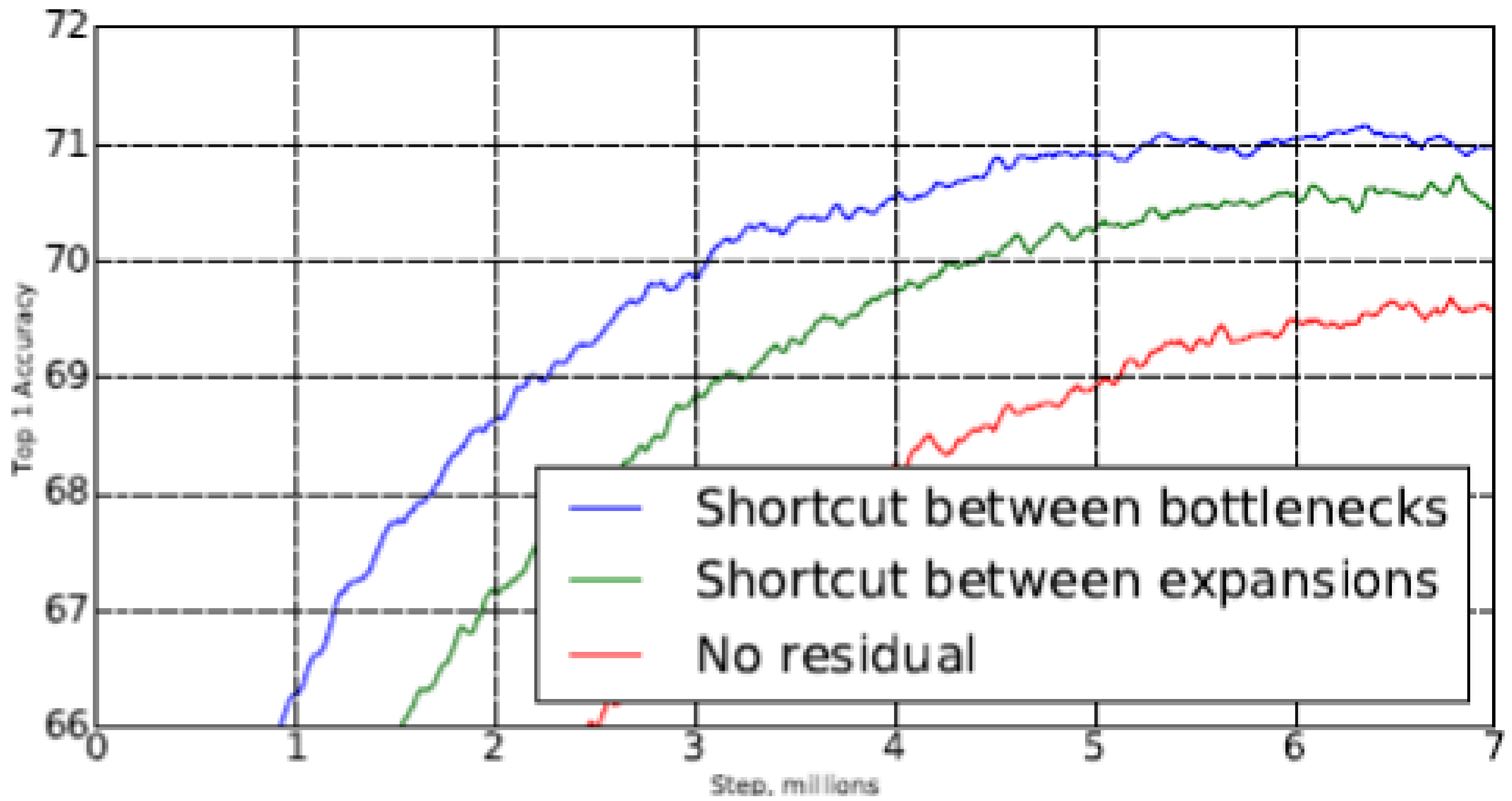
ABLATION STUDY

Impact of Linear Bottleneck



With the removal of ReLU6 at the output of each bottleneck module, accuracy is improved.

Impact of Shortcut:



With shortcut between bottlenecks, it outperforms shortcut between expansions and the one without any residual connections.

Conclusion

- In conclusion, this project aims to develop a deep learning model for improved detection of gallbladder stones in ultrasound images. The proposed approach involves a two-phase technique - gallbladder region extraction followed by a specialized second order pooling CNN architecture for stone classification.
- Key innovations include optimizing the model to handle image noise and artifacts, as well as introducing curriculum learning to reduce texture bias. The model will be evaluated on the GBCU ultrasound image dataset.
- The goal is to demonstrate enhanced accuracy compared to current state-of-the-art methods and human experts. If successful, this cost-effective and accessible solution can be integrated into clinical practice to improve gallbladder stone diagnosis.

Conclusion

- Further validation on larger datasets, testing generalization capability, and optimizations for small stone detection represent areas for future work. There is immense potential for this technology to benefit healthcare by improving diagnostic precision, reducing costs, and increasing accessibility.
- In summary, this project aims to push the boundaries of medical imaging to tackle a clinically significant problem - missed or inaccurate gallbladder stone detection. The innovations proposed represent a promising step towards intelligent systems that can surpass human experts.

Thank you!