# 1 Summary
## 1.1 Motivation
This research addresses the critical need for enhanced breast cancer prediction by exploring ensemble methods, specifically employing the ensembled LeNet CNN. With the overarching aim of contributing a modified LeNet model surpassing existing architectures in accuracy, the hypothesis posits that integrating ensemble methods and modifying LeNet can significantly elevate breast cancer prediction accuracy.

## 1.2 Contribution
This study's primary contribution is a superior modified LeNet model for breast cancer prediction. It outperforms state-of-the-art CNNs in accuracy, precision, recall, and F1 score. Beyond the model, the study offers a systematic approach, integrating ensemble techniques, hyperparameter tuning, and rigorous data preprocessing for effective breast cancer prediction.

## 1.3 Methodology
The study employs a meticulous methodology, commencing with the thorough preprocessing of the Breast Ultrasound (BUS) dataset, encompassing image resizing, pixel value normalization, and strategic data partitioning. Multiple LeNet CNN models are then trained with diverse initialization and hyperparameter settings, emphasizing the significance of ensemble methods, hyperparameter optimization, and precise data preprocessing. Notably, the LeNet architecture is modified to enhance its predictive capabilities, incorporating ensemble methods, ReLU activation function, and 40% dropout. The training process incorporates soft voting, a sophisticated ensemble technique, and early stopping to prevent overfitting. This systematic approach aims at bolstering the breast cancer prediction model's accuracy and generalizability, reflecting the study's commitment to methodological rigor.

## 1.4 Conclusion
The study concludes with the successful demonstration of the ensembled LeNet model's superiority in breast cancer prediction. The modified LeNet exhibits commendable accuracy, precision, recall, and F1 score, affirming its effectiveness in medical image classification. The conclusion underscores the significance of ensemble methods and hyperparameter tuning in achieving these results. This research sets the stage for future advancements in medical image classification, with implications for improving diagnostic accuracy.

# 2 Limitations
## 2.1 First Limitation
One significant limitation of this study pertains to the dataset's size and representativeness. The relatively small dataset employed might constrain the model's ability to generalize effectively. A more extensive and diverse dataset would be instrumental in providing a more comprehensive and reliable evaluation of the proposed breast cancer prediction model.

## 2.2 Second Limitation
Another noteworthy limitation involves the sensitivity of hyperparameter tuning. The model's performance is highly influenced by subtle adjustments in hyperparameters, raising concerns about its stability and generalizability across diverse datasets and clinical scenarios. The study acknowledges the intricacies of hyperparameter sensitivity and emphasizes the need for further investigation to enhance the model's robustness.

# 3 Synthesis
The research introduces a novel approach to breast cancer prediction through an ensembled LeNet convolutional neural network (CNN). Motivated by the imperative to enhance diagnostic accuracy in medical imaging, the study formulates an ensemble of thirteen LeNet models, surpassing individual architectures and rivaling state-of-the-art CNNs. The methodology involves meticulous preprocessing of the breast ultrasound (BUS) dataset, training diverse LeNet models with distinct initialization and hyperparameter settings, and combining their predictions using soft voting. The resulting model achieves an accuracy of 89.91%, outperforming traditional LeNet and other preeminent CNNs. The contribution lies in not only the heightened accuracy but also the exploration of ensemble methods in the medical imaging domain. While acknowledging limitations, including the need for extensive hyperparameter tuning, the synthesis of this work envisions practical applications in computer-aided diagnosis and propels future research by advocating for the integration of ensemble learning in evolving medical imaging landscapes.