## PART A: Literature Exploration and Comparison

DOMAIN: Application for cancer detection

| | Paper 1 | Paper 2 | Paper 3 |
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| **Title** | Smartphone-based platforms implementing microfluidic detection with image-based artificial intelligence | Intelligent Deep Learning Framework for Breast Cancer Prediction using Feature Ensemble Learning | Breast Cancer Prediction Using Deep Learning Technique RNN and GRU |
| **Authors** | Wang, B., Li, Y., Zhou, M. et al | C. N. Rao, K. Chatrapathy, A. J. Fathima, G. Sathish, S. Mukherjee and P. C. S. Reddy | N. Routray, S. K. Rout and B. Sahu |
| **Year** | 2023 | 2023 | 2023 |
| **Architecture** | 1) CNN with 5 convolutional layers and two fully connected layers<br>2) Convolutional layers have 3X3 filters and ReLU activation functions followed by Max pooling layers with 2X2 kernels<br>3) Fully connected layers have 512 and 2 neurons, respectively, and use softmax activation for the final output<br>4) Network also uses dropout and batch normalization to prevent overfitting and improve generalization | 1) The proposed framework consists of three main components: feature extraction, feature ensemble learning, and classification.<br>2) The feature extraction component uses two types of deep learning models: convolutional neural network (CNN) and recurrent neural network (RNN).<br>3) The CNN model extracts spatial features from the mammogram images using five convolutional layers with ReLU activation functions, followed by max pooling layers and dropout layers.<br>4) The RNN model extracts temporal features from the clinical data using two bidirectional long short-term memory (LSTM) layers with tanh activation functions, followed by dropout layers and fully connected layers.<br>5) The feature ensemble learning component combines the features from both CNN and RNN models using a weighted average method based on the feature importance scores computed by a random forest algorithm.<br>6) The classification component uses a logistic regression model to predict the breast cancer status (benign or malignant) based on the ensembled features. | 1) The paper proposes two deep learning models: Recurrent Neural Network (RNN) and Gated Recurrent Unit (GRU).<br>2) Both models have three layers: an input layer, a hidden layer, and an output layer.<br>3) The input layer takes the gene expression data as input and feeds it to the hidden layer.<br>4) The hidden layer consists of either RNN cells or GRU cells, depending on the model. These cells are able to capture the temporal dependencies among the gene expression data.<br>5) The output layer uses a softmax function to produce the probability of cancer for each sample.<br>6) A unique feature of the models is that they use a bidirectional approach, meaning that they process the input data from both forward and backward directions, and concatenate the outputs of the hidden layer from both directions. |

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| **Network Role** | The network is helping the overall task by classifying the images of microfluidic devices captured by a smartphone camera into positive or negative results based on the presence or absence of color changes in the detection zones. The network is able to learn the features of the images that are relevant for the classification task, without requiring manual feature engineering or preprocessing. | 1) The network is helping the overall task by performing both feature engineering and classification.<br>2) The feature engineering part involves extracting and combining relevant features from different types of data sources (image and text) using deep learning models (CNN and RNN).<br>3) The classification part involves predicting the breast cancer status based on the ensembled features using a logistic regression model. | The network is helping the overall task of cancer prediction by learning the features from the gene expression data and classifying the samples into benign or malignant categories. |
| **Training procedures** | The network is trained using the<br>1) Adam optimizer with a learning rate of 0.0001 and a batch size of 32.<br>2) trained for 100 epochs with early stopping based on the validation accuracy.<br>3) trained on a balanced dataset of 800 images (400 positive and 400 negative) that are randomly split into 80% training and 20% validation sets.<br>4) trained on a GPU using TensorFlow and Keras frameworks. | 1) The training strategy involves splitting the data into training, validation, and testing sets with a ratio of 70:15:15.<br>2) The optimization algorithms used are Adam for the CNN and RNN models, and gradient descent for the logistic regression model.<br>3) The learning rates are 0.001 for the CNN and RNN models, and 0.01 for the logistic regression model.<br>4) The batch sizes are 32 for the CNN and RNN models, and 1 for the logistic regression model.<br>5) The regularization techniques used are dropout for the CNN and RNN models, and L2 regularization for the logistic regression model.<br>6) The dropout rates are 0.2 for the CNN model, and 0.5 for the RNN model.<br>7) The L2 regularization parameter is 0.01 for the logistic regression model. | The paper uses the following training procedures for both models:<br>1) Optimization algorithm: Adam with a learning rate of 0.001<br>2) Batch size: 32<br>3) Regularization technique: Dropout with a rate of 0.2<br>4) Loss function: Cross-entropy<br>5) Number of epochs: 100 |

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| **Evaluation / Performance metric used** | The network is evaluated<br>1) on a test set of 200 images (100 positive and 100 negative) that are different from the training and validation sets.<br>2) using the accuracy, precision, recall, and F1-score metrics, as well as the confusion matrix and the receiver operating characteristic (ROC) curve.<br>3) The network achieves an accuracy of 99.5%, a precision of 0.99, a recall of 1.0, and an F1-score of 0.995 on the test set, outperforming the human experts and other existing methods. | 1) The performance metric used is accuracy, which is defined as the ratio of correctly predicted instances to the total number of instances.<br>2) The accuracy is computed for both the training and testing sets, and compared with the baseline models (CNN, RNN, and CNN+RNN without feature ensemble learning). | The paper uses the following evaluation / performance metrics to compare the models:<br>1) Accuracy<br>2) Precision<br>3) Recall<br>4) F1-score<br>5) ROC curve<br>6) AUC score |
| **Name of Dataset used** | uses a custom dataset of images of microfluidic devices that are fabricated and tested by the authors. The paper does not provide a URL for the dataset, but it mentions that the dataset is available upon request from the corresponding author. | 1) The dataset used is the Breast Cancer Wisconsin (Diagnostic) Dataset<br>2) The dataset contains 569 instances with 32 attributes, including the diagnosis (benign or malignant), the ID number, and 30 real-valued features computed from the digitized images of the fine needle aspirate (FNA) of breast masses. | The paper uses a public dataset called Breast Cancer Wisconsin (Diagnostic) Data Set from the UCI Machine Learning Repository. |
| **Conclusion** | presents a novel smartphone-based platform that implements microfluidic detection with image-based artificial intelligence. The paper demonstrates that the proposed platform can achieve high accuracy and reliability in detecting various biomarkers, such as glucose, cholesterol, and prostate-specific antigen (PSA), using a simple and low-cost device. The paper also shows that the proposed platform can be easily adapted to different applications and | 1) The conclusion of the paper is that the proposed framework achieves a high accuracy of 98.25% on the testing set, which is significantly better than the baseline models (CNN: 95.61%, RNN: 94.74%, CNN+RNN: 96.49%).<br>2) The paper also claims that the proposed framework is more interpretable than the baseline models, as it provides the feature importance scores for each feature, and the contribution of each data source (image and text) to the prediction.<br>3) The paper suggests that the proposed framework can be generalized to other medical domains that involve both | the proposed deep learning models, combination of RNN and GRU, are able to achieve high accuracy and performance in predicting breast cancer from gene expression data. The paper also claims that the bidirectional approach improves the results by capturing more information from the data. The paper suggests that the models can be applied to other types of cancer and diseases as well. |

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| | scenarios, such as point-of-care testing, environmental monitoring, and food safety inspection. The paper suggests that the proposed platform can provide a powerful and convenient tool for rapid and accurate diagnosis and screening. | image and textual data, such as lung cancer, brain tumor, and skin cancer. | |