Practical Data Science

COSC2789 - Dr Thuy Nguyen

Teams 2:

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I. Introduction

Introduction

In **2022**, it is estimated that more than **18.1 million** cases of cancer are recorded worldwide [1]. Cancer prevention is one of the **most crucial and foremost** public health concerns of modern society, due to its **rapid growth rate and limitation in cure**.

Introduction

Colorectal Cancer, or ‘Colon’ cancer for short, is a disease where **cells within the rectum or colon** of a human body **multiplies and grows at an uncontrollable rate** [8]. It is one of the top three most popular forms of cancer worldwide [9].

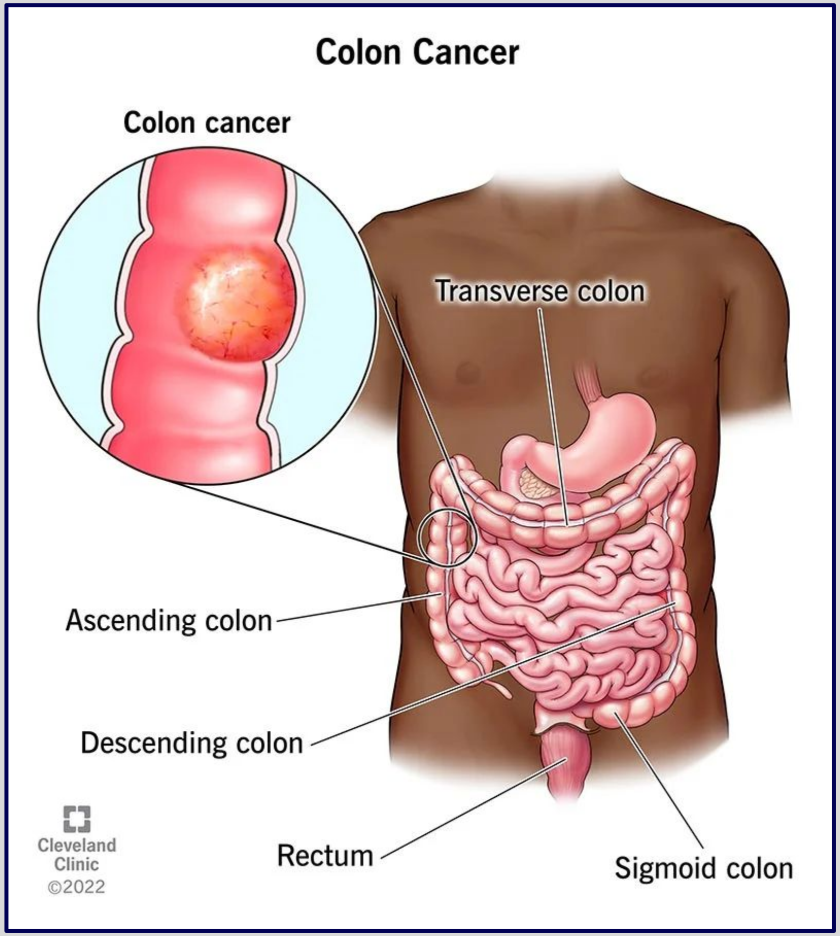
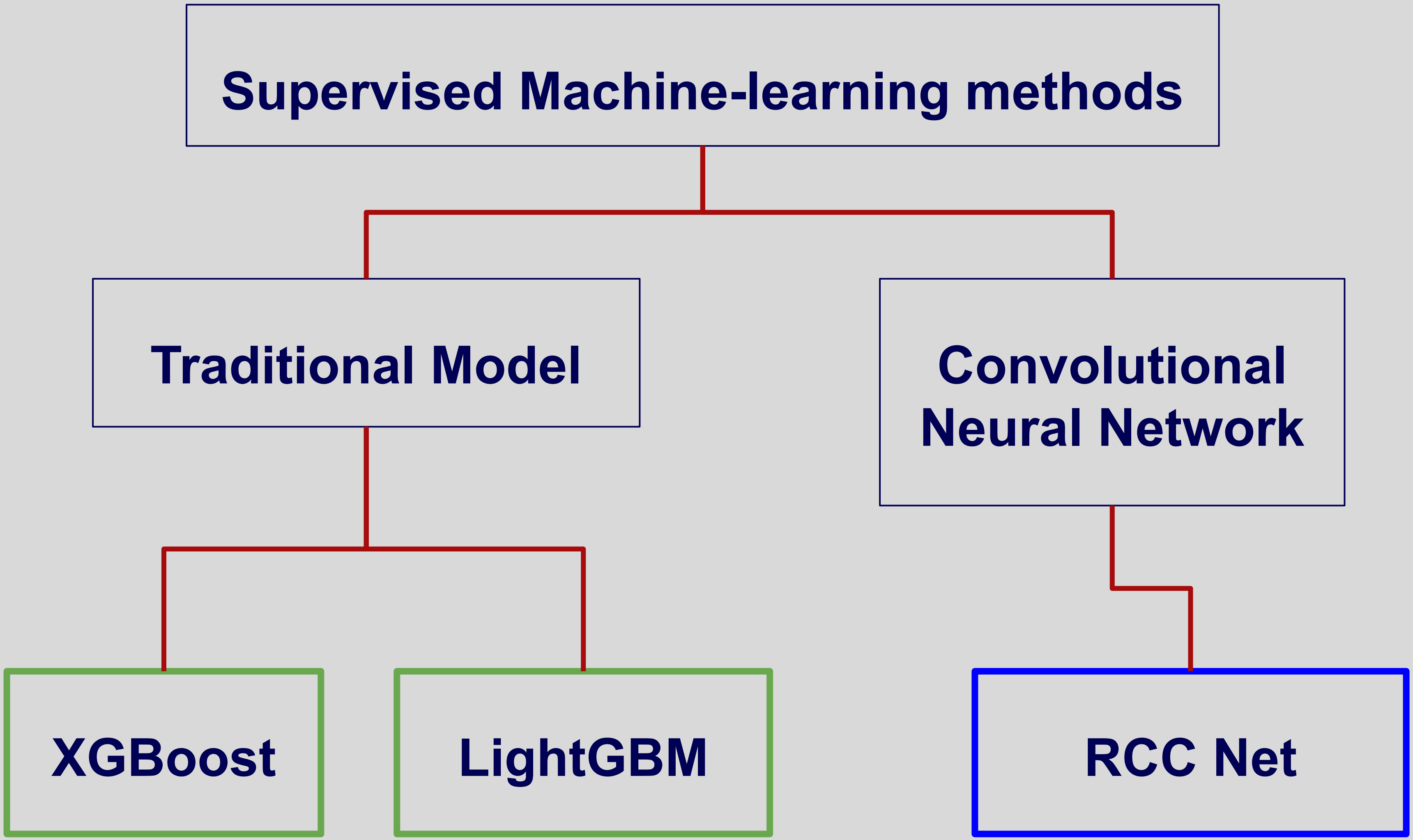


Fig 1.1: Colon cancer anatomy layout

Introduction



Dataset (Main data)

6 Columns &
9896 Columns

4 Types: firoblase, inflammatory, epithelial, others

data_labels_mainData

InstanceID	patientID	ImageName	cellTypeName	cellType	isCancerous
22405	1	22405.png	fibroblast	0	0
22406	1	22406.png	fibroblast	0	0
22407	1	22407.png	fibroblast	0	0
22408	1	22408.png	fibroblast	0	0
22409	1	22409.png	fibroblast	0	0
22410	1	22410.png	fibroblast	0	0

Row ID

Fig 1.2: first 6 rows of main data set [2]

Unique to each patient

0 (false)
1 (true)

Dataset (Extra)

4 Columns & 10384 Rows

data_labels_extraData

InstanceID	patientID	ImageName	isCancerous
12681	61	12681.png	0
12682	61	12682.png	0
12683	61	12683.png	0
12684	61	12684.png	0
12685	61	12685.png	0

Fig 1.3: first 5 rows of extra data set [2]

Row ID

0 (false)
1 (true)

Unique to each patient

II. Methodology

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Data pipeline

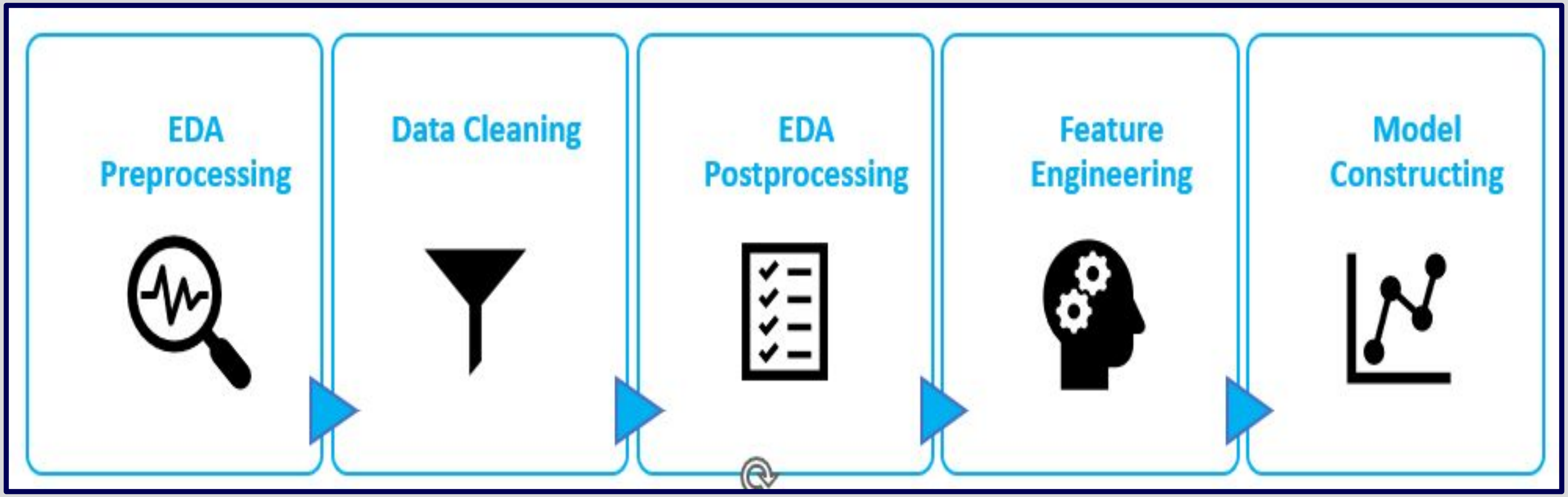

Fig 2.1: Data Pipeline visualization

Traditional Machine Learning models

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XGBOOST Explanation

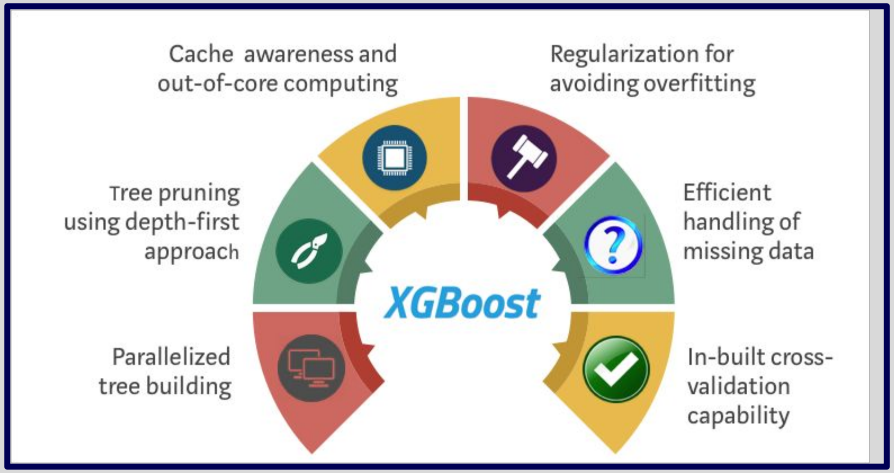


Fig 3.1: XGBoost features visualization

Extreme Gradient Boosting (XGBoost) is a **distributed, scalable gradient-boosted decision tree** (GBDT) machine learning framework.

It's consider to be one of the top machine learning library for **regression, classification, and ranking issues**, it offers parallel tree boosting [3].

XGBOOST

The XGBOOST Library is the implementation of Gradient Boosting algorithm.

Boosting is a modeling approach combining several weak tree based classifiers, with aims to create a high performance classifier.

In gradient boosting, **each classifiers correct it's predecessor error**. Additionally each classifier is trained using the residual errors of predecessor as labels

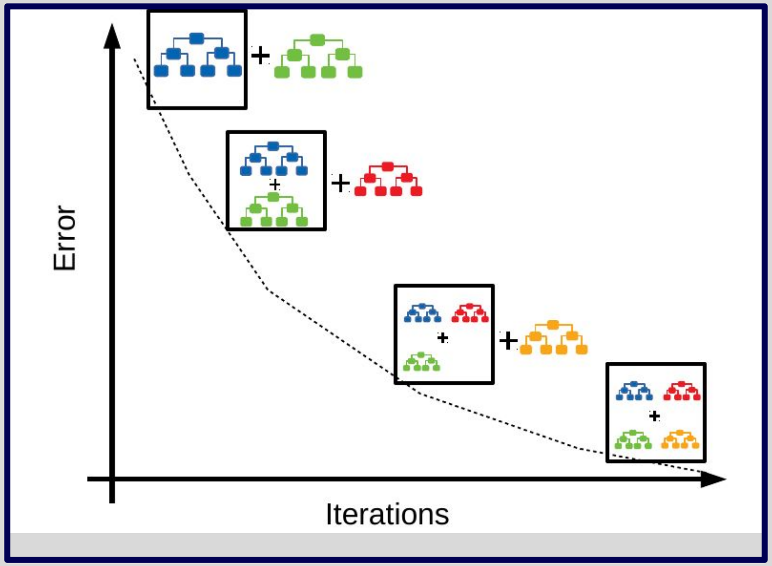


Fig 3.2: ___

LightGBM

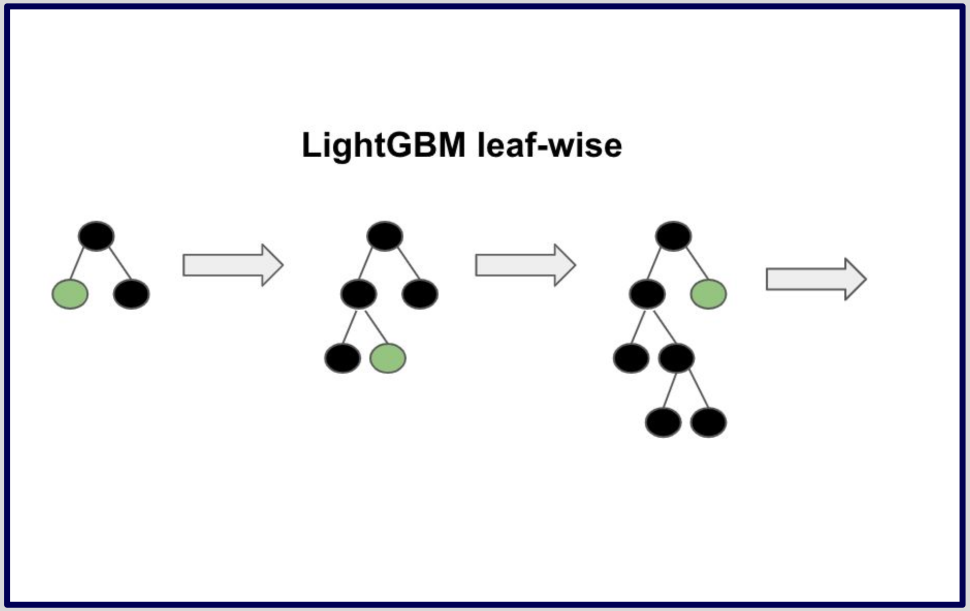


Fig 4.1: LightGBM leaf-wise grow

LightGBM (short for Light Gradient Boosting Machine), is a framework that use **tree-based learning algorithms** [4]**.** It grows the decision tree **leaf-wise** (vertically) which differs than other boosting algorithms where they grows depth-wise (horizontally) [5].

LightGBM

It can handle large datasets and is **faster** than other popular libraries (ex: XGBoost).

LightGBM includes unique features [10]:

+ Support for categorical features

+ Efficient handling of missing values

+ Support for parallel processing.

Convolutional Neural Network

Convolutional Neural Network

CNN (short for Convolutional Neural Network) is a type of **deep learning model** for processing data that has a **grid pattern**, such as images [6].

It can deal with **2D image classification** problems with **higher accuracy.**

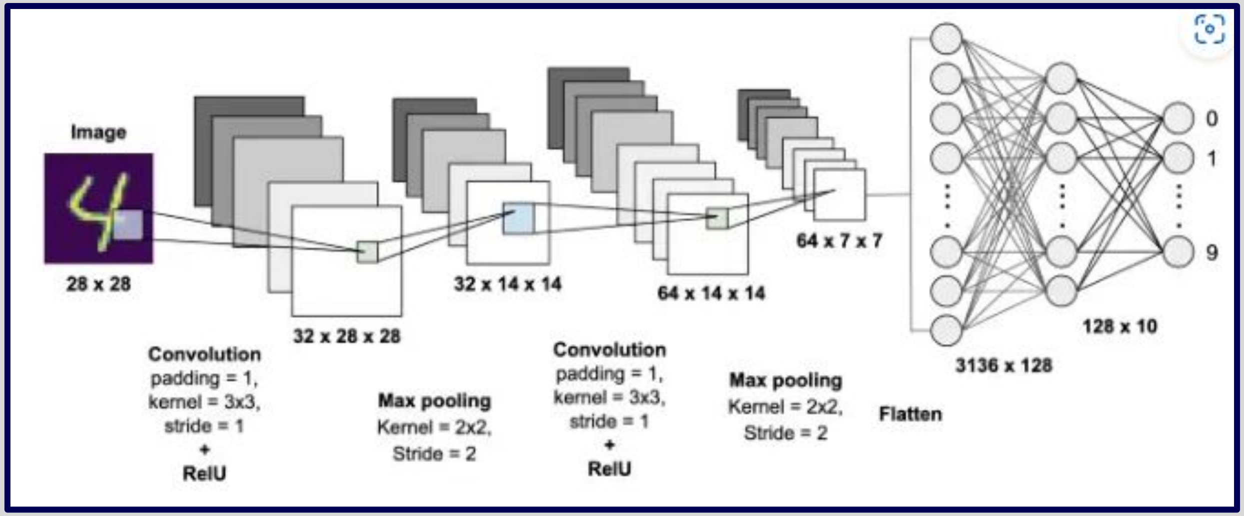


Fig 5.1: CNN deep learning visualization

RCC NET

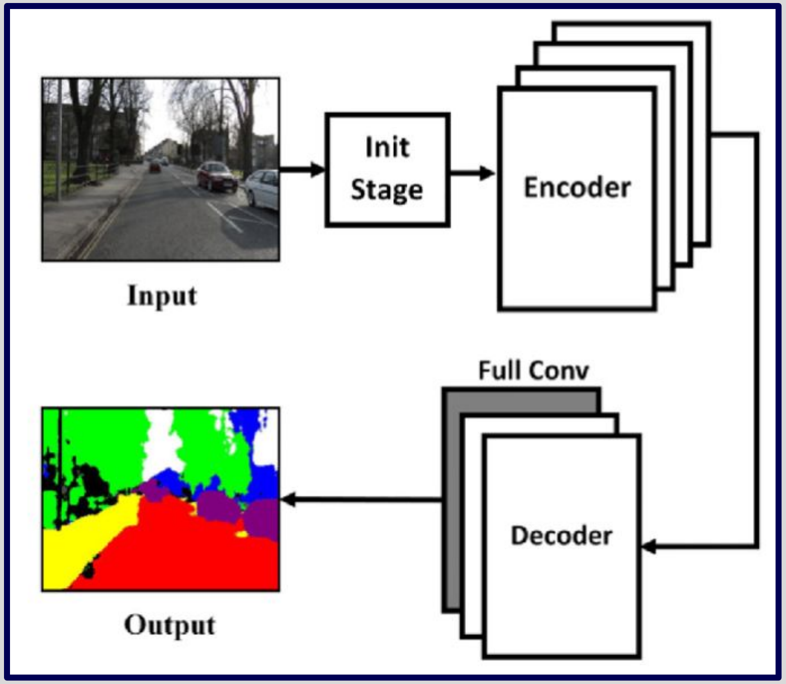


Fig 5.2: ____

RCC Net is a deep learning model (CNN based architecture).

RCC-Net performs dimensionality reduction to compress and extract relevant feature.

ENSEMBLE MODEL

Our **ensemble classifier** of choice is a **VotingClassifier** provided in Scikit learn library.

Inspired by the concept of Boosting, the team wanted to create a new model based on the combination of high performances.

The submodels a chance to “vote” the probability of the output result. The weights of the “vote” can be modified [7].

ENSEMBLE MODEL

The model start with a **scaler** (MinMax scaler).

The post scaling data then pass through the **Voting Classifier** ensemble model consisting of a **tuned LightGBM** classifier and **XGBoost Classifier** for training and classification.

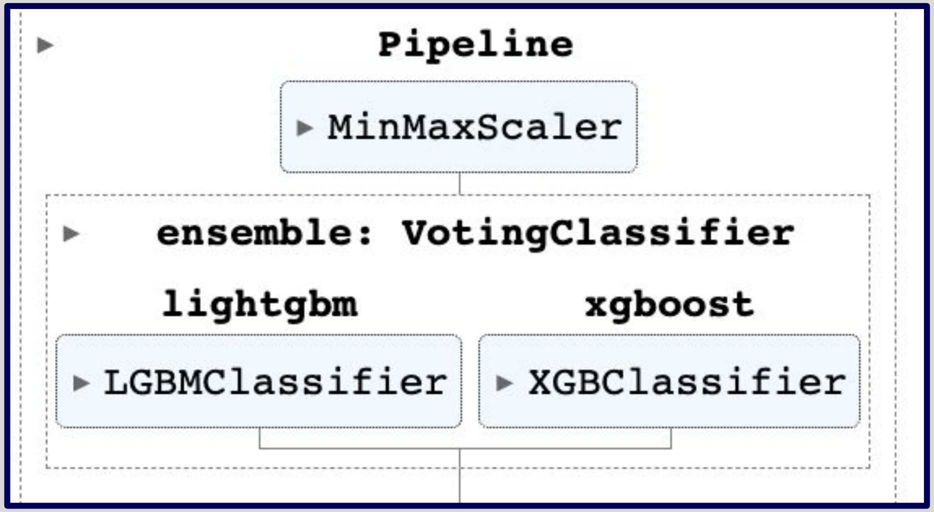


Fig 6.1: Ensemble model visualization

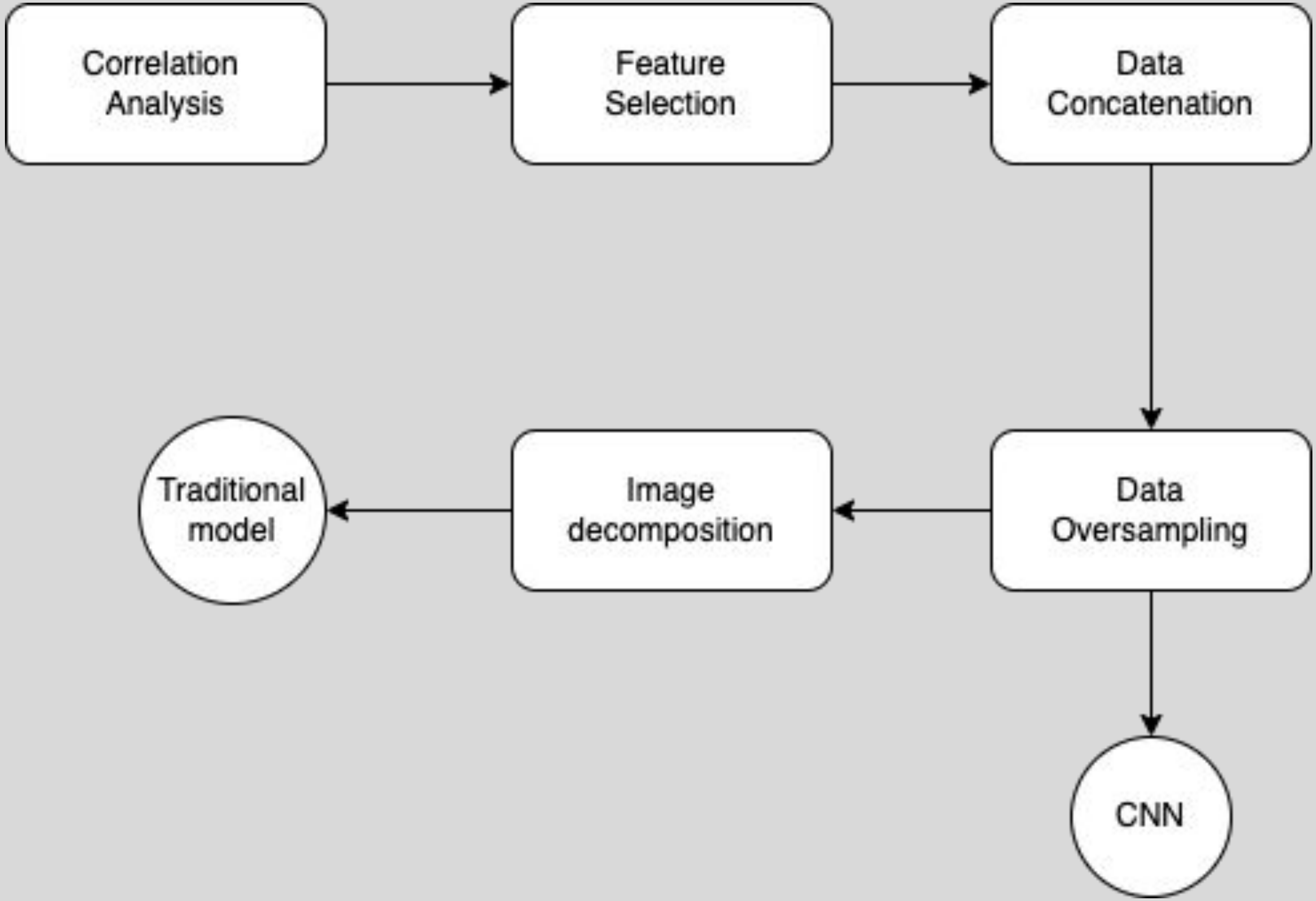
III. Feature Engineering

EDA [Pre & Post Processing]

Hypotheses to be examined (apply for both **before** and **after** processing the data):

- **Hypothesis 1:** Cell type 2 is the only cancerous cell
- **Hypothesis 2:** Cell type 2 have the highest frequency
- **Hypothesis 3:** Cancerous cells account for over 50%
- **Hypothesis 4:** The percentage of images being identified as cancerous for each patientID will be over 50%

Feature Engineering



Feature Engineering

Main data set:
'celltype' and 'patientid' are correlated with the 'iscancerous' column.

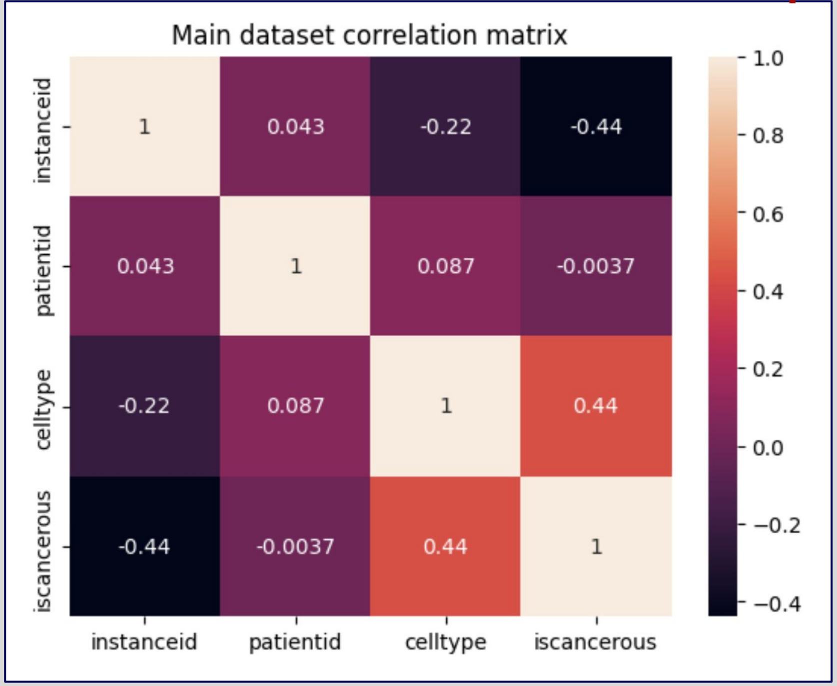


Fig 7.1: Main Data correlation matrix

Extra data set:
'patientid' and 'instanceid' are correlated with the 'iscancerous' column.

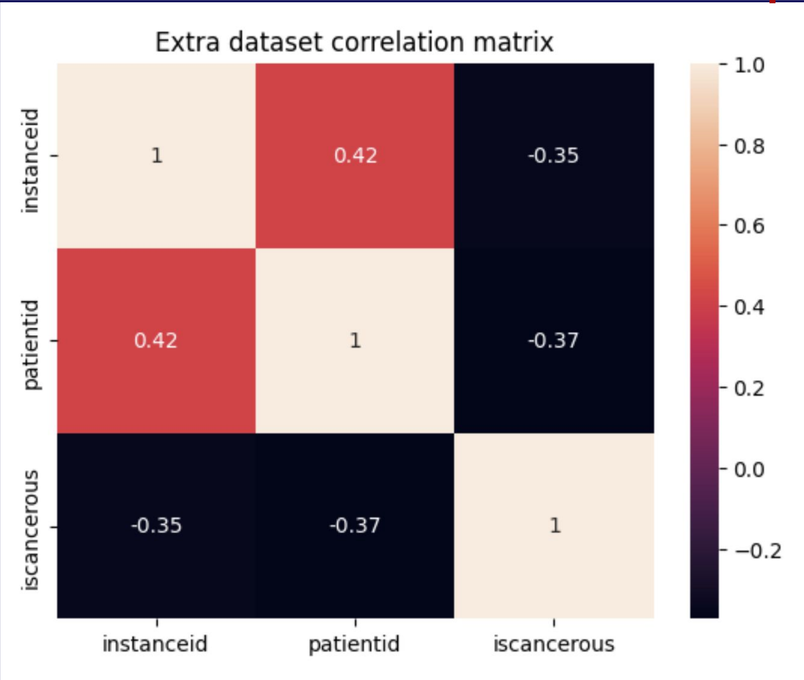


Fig 7.2: Extra Data correlation matrix

Feature Engineering

Main data set:
'imagename', 'iscancerous' and 'celltype' is selected,
The remaining columns is dropped to prevent data leakage.

```
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   imagename    9803 non-null   object
 1   celltype     9803 non-null   int64
 2   iscancerous  9803 non-null   int64
dtypes: int64(2), object(1)
memory usage: 229.9+ KB
```

Fig 7.3: Main data set columns selection for modeling

Extra data set:
'iscancerous' and 'imagename' is selected.

```
Int64Index: 20097 entries, 0 to 20096
Data columns (total 2 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   imagename    20097 non-null  object
 1   iscancerous  20097 non-null  int64
dtypes: int64(1), object(1)
memory usage: 471.0+ KB
```

Fig 7.4: Extra data set columns selection for modeling

Data Concatenation

Both extra and main dataset have ‘iscancerous’, and ‘imagename’

=> A **new dataset is created** by **concatenate** two feature of the two dataset:

- In order to increase the size of a dataset
- Enhancing the performance of the model

Over Sampling

Using **SMOTE** from imbalanced learn library. The dataset is for **task 1**.

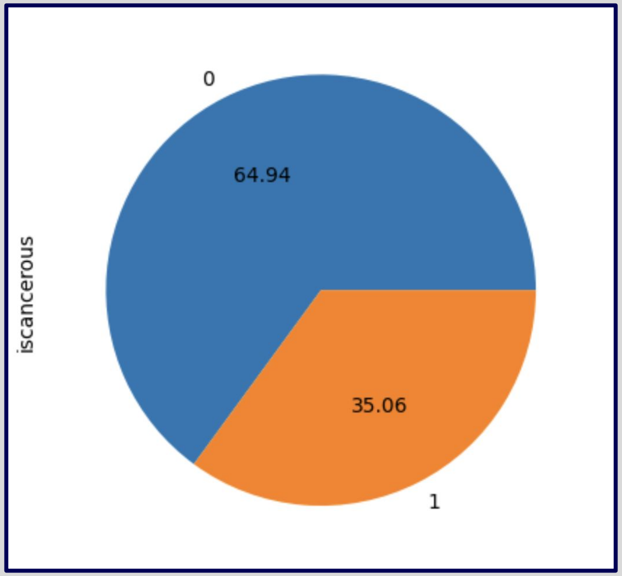


Fig 7.5: Before over sampling for task 1

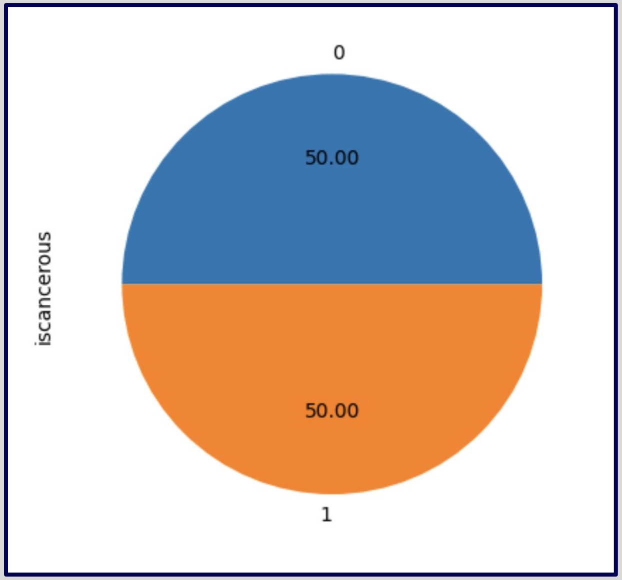


Fig 7.6: After over sampling for task 1

Over Sampling

Using **SMOTE** from imbalanced learn library. The dataset is for **task 2**.

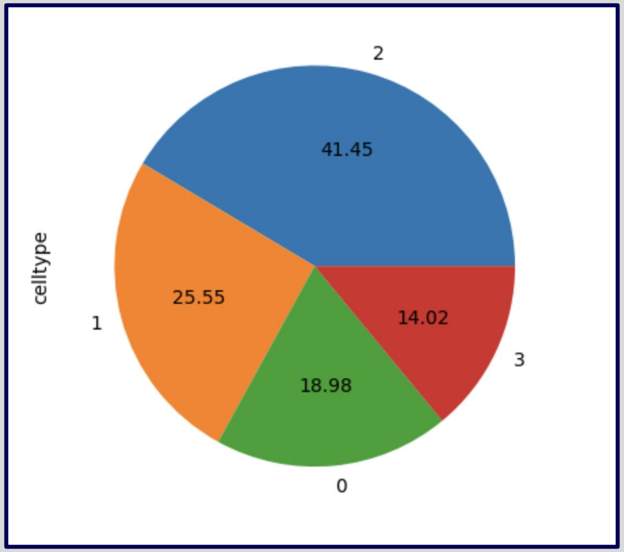


Fig 7.7: Before over sampling for task 2

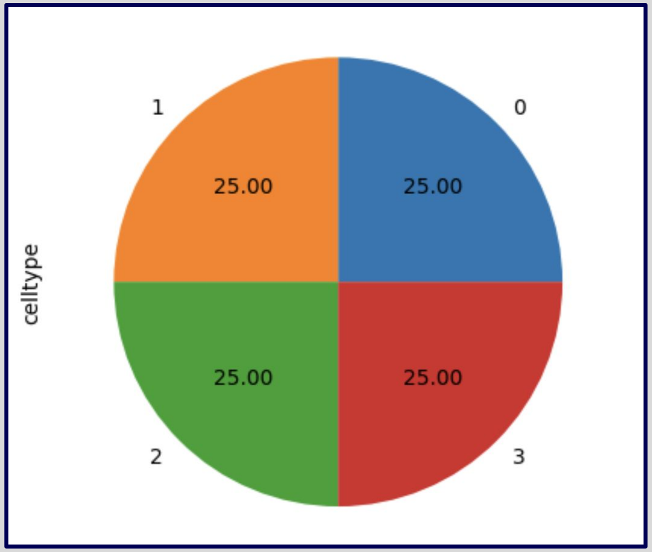


Fig 7.8: After over sampling for task 2

Image Decomposition

Images in **raw format** are **not compatible** with traditional machine learning framework.

- The 27x 27 x 3 size image is unravel into pixel with numerical features.

Fig 8.1: Example of a cancer cell image

Visualize

iscancerous int64 0 - 1	p0 uint8 38 - 255	p1 uint8 14 - 255	p2 uint8	p3 uint8	p4 uint8
0	198	151	196	204	158
0	220	193	228	216	189
0	255	226	249	255	234
0	231	191	233	196	152
0	212	179	220	199	164
0	191	138	190	203	151

Fig 8.2: Numerical features from pixel image

IV. Results

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Tuned XGBOOST results

Task 1: Tuned XGBooost

```
Model accuracy for train set: 1.000
Model accuracy for test set: 0.926

              precision    recall  f1-score   support

           0       0.94      0.91      0.92      3915
           1       0.91      0.94      0.93      3915

    accuracy                           0.93      7830
   macro avg       0.93      0.93      0.93      7830
weighted avg       0.93      0.93      0.93      7830
```

Fig 9.1: XGBoost accuracy score (task 1)

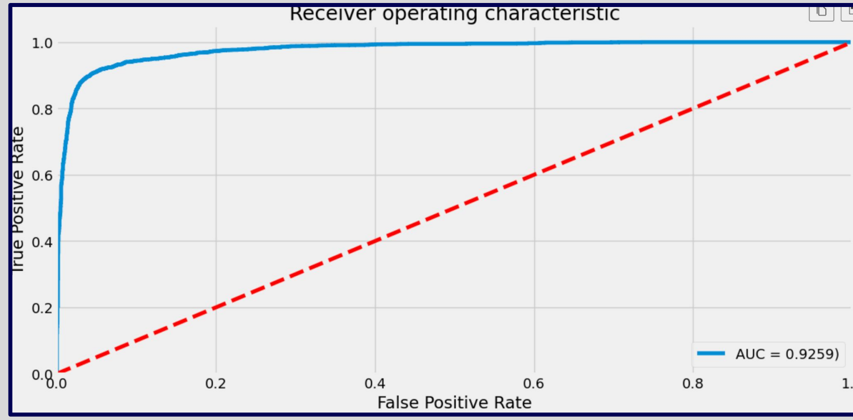

Fig 9.2: Tuned XGBoost ROC Curve (task 1)

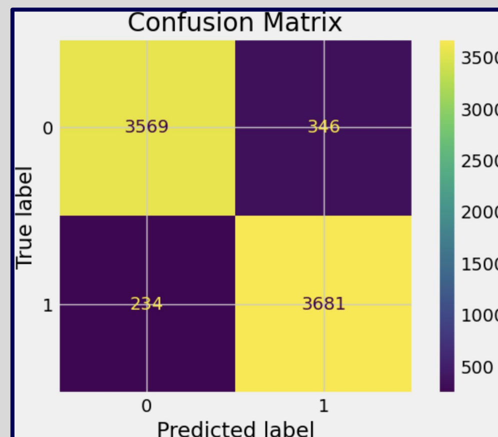

Fig 9.3: XGBoost Confusion Matrix (task 1)

Tuned XGBOOST results

Task 2: Tuned XGBooost

```
Model accuracy for train set: 1.000
Model accuracy for test set: 0.911
```

	precision	recall	f1-score	support
0	0.90	0.95	0.93	1219
1	0.87	0.89	0.88	1219
2	0.92	0.89	0.91	1219
3	0.96	0.91	0.93	1219
accuracy			0.91	4876
macro avg	0.91	0.91	0.91	4876
weighted avg	0.91	0.91	0.91	4876

Fig 9.4: XGBoost accuracy score (task 2)

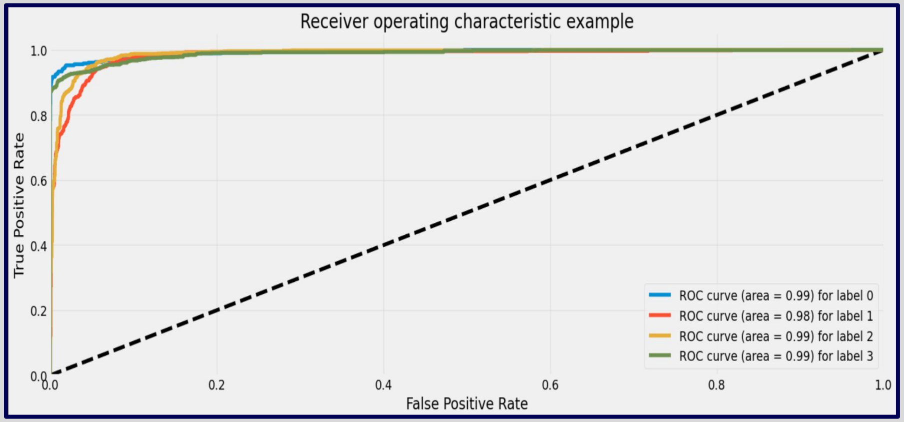

Fig 9.5: XGBoost ROC Curve (task 2)

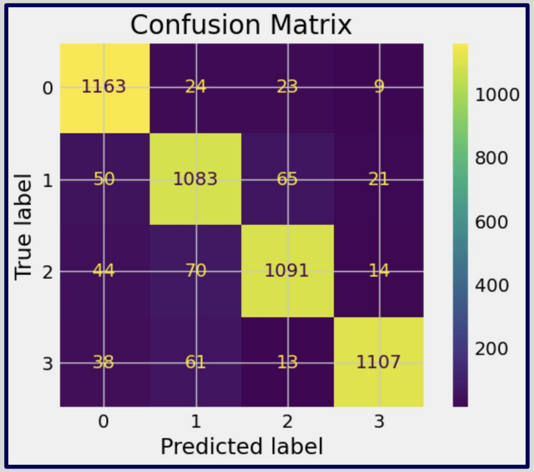

Fig 9.6: XGBoost confusion matrix (task 2)

Tuned LightGBM results

Task 1: Tuned LightGBM

```
Model accuracy for train set: 0.979
Model accuracy for test set: 0.912

              precision    recall  f1-score   support

           0       0.92      0.90      0.91      3915
           1       0.90      0.93      0.91      3915

    accuracy                           0.91      7830
   macro avg       0.91      0.91      0.91      7830
weighted avg       0.91      0.91      0.91      7830
```

Fig 9.7: Tuned LightGBM accuracy score (task 1)

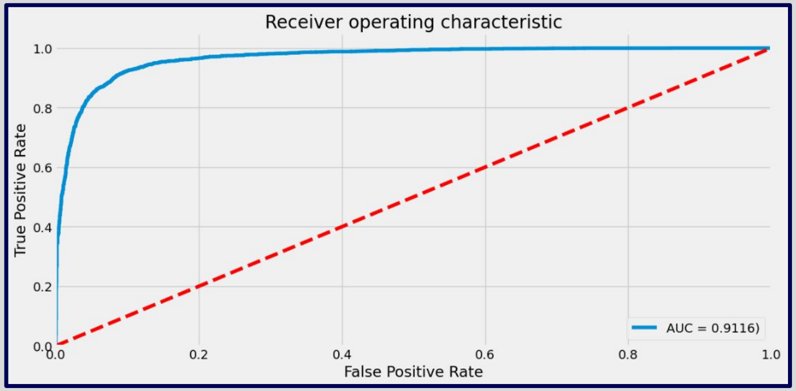

Fig 9.8: Tuned LightGBM ROC curve (task 1)

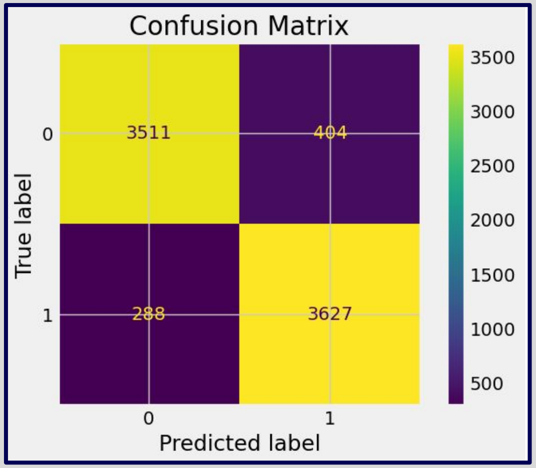

Fig 9.9: Tuned LightGBM confusion matrix (task 1)

Tuned LightGBM results

Task 2: Tuned LightGBM

```
Model accuracy for train set: 1.000
Model accuracy for test set: 0.914

              precision    recall  f1-score   support

           0       0.91      0.96      0.93      1219
           1       0.88      0.89      0.89      1219
           2       0.92      0.90      0.91      1219
           3       0.96      0.90      0.93      1219

    accuracy                           0.91      4876
   macro avg       0.91      0.91      0.91      4876
weighted avg       0.91      0.91      0.91      4876


Confusion Matrix:
 [[1169   19   17   14]
 [  44 1089   61   25]
 [  44   68 1095   12]
 [  34   66   17 1102]]

Accuracy Score:  0.914
```

Fig 9.10: Tuned LightGBM accuracy score (task 2)

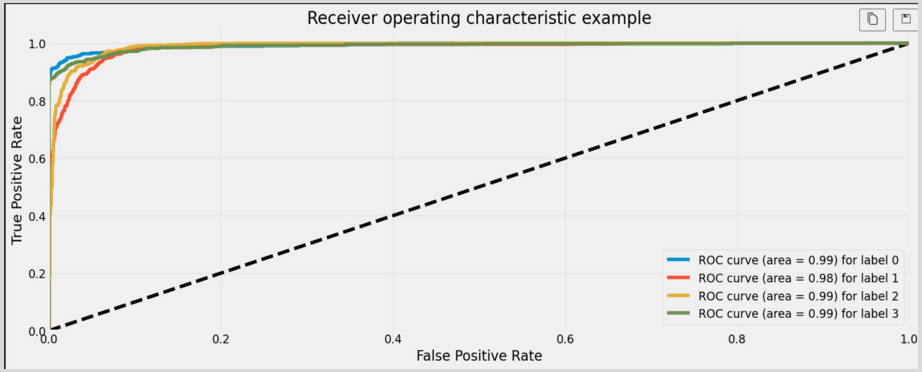

Fig 9.11: Tuned LIghtGBM ROC Curve (task 2)

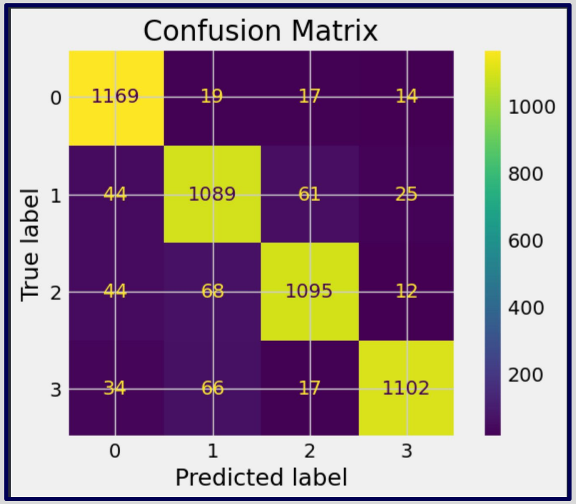

Fig 9.12: Tuned LightGBM confusion matrix (task 2)

Tuned RCC-net results

Task 1: Tuned RCC-net

```
Model Evaluation
---------------------------------------------
loss - test: 0.18401867151260376
loss - train : 0.09642554074525833
loss - val: 0.1682843416929245
---------------------------------------------
accuracy - test: 0.9329643249511719
accuracy - train : 0.9667692184448242
accuracy - val: 0.9483076930046082
---------------------------------------------
recall - test: 0.9310897588729858
recall - train : 0.9657047986984253
recall - val: 0.9473039507865906
---------------------------------------------
precision - test: 0.9324603080749512
precision - train : 0.967363715171814
precision - val: 0.9491523504257202
---------------------------------------------
f1 - test: 0.9317014217376709
f1 - train : 0.9664754271507263
f1 - val: 0.9481966495513916
```

Fig 9.13: Tuned RCC_net accuracy score (task 1)

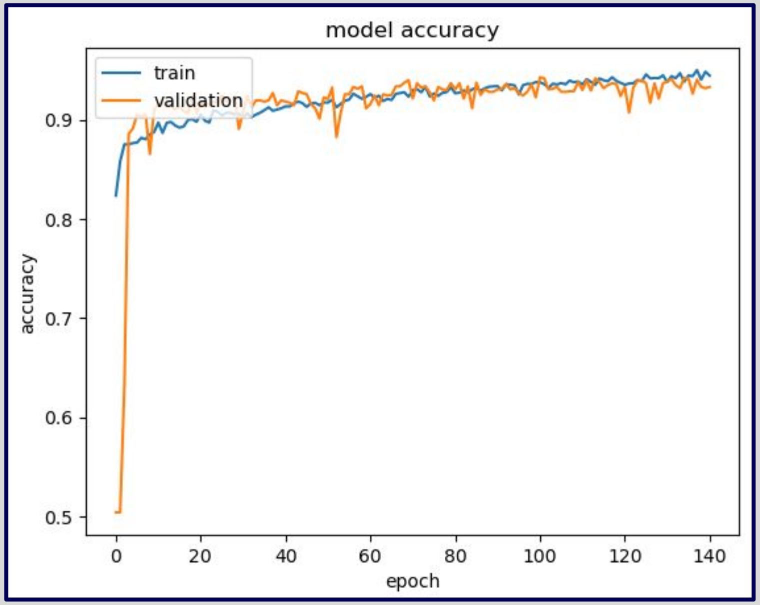

Fig 9.14: Tuned RCC_net model accuracy (task 1)

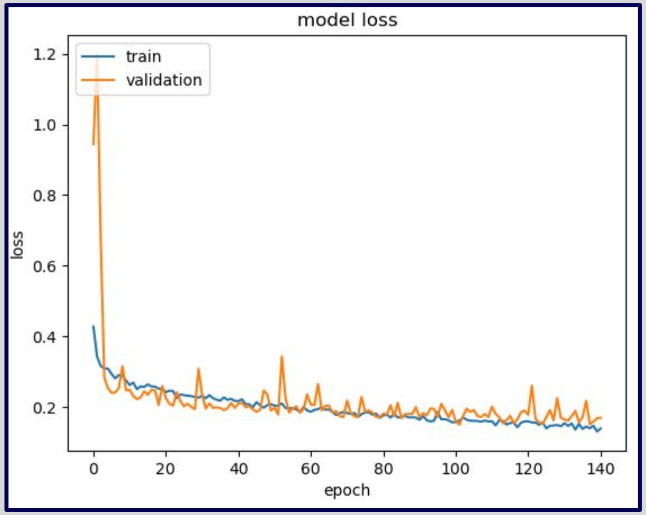

Fig 9.15: Tuned RCC_net model loss (task 1)

Tuned RCC-net results

Task 2: Tuned RCC-net

```
Model Evaluation
---------------------------------------------
loss - test: 0.3998308479785919
loss - train : 0.3382495045661926
loss - val: 0.3680887520313263
---------------------------------------------
accuracy - test: 0.8603506684303284
accuracy - train : 0.8728204965591431
accuracy - val: 0.876038134098053
---------------------------------------------
recall - test: 0.8403637409210205
recall - train : 0.8450912833213806
recall - val: 0.8542472720146179
---------------------------------------------
precision - test: 0.8802827596664429
precision - train : 0.8960369229316711
precision - val: 0.8930943012237549
---------------------------------------------
f1 - test: 0.8595331311225891
f1 - train : 0.869326114654541
f1 - val: 0.8728362917900085
```

Fig 9.16: Tuned RCC_net accuracy score (task 2)

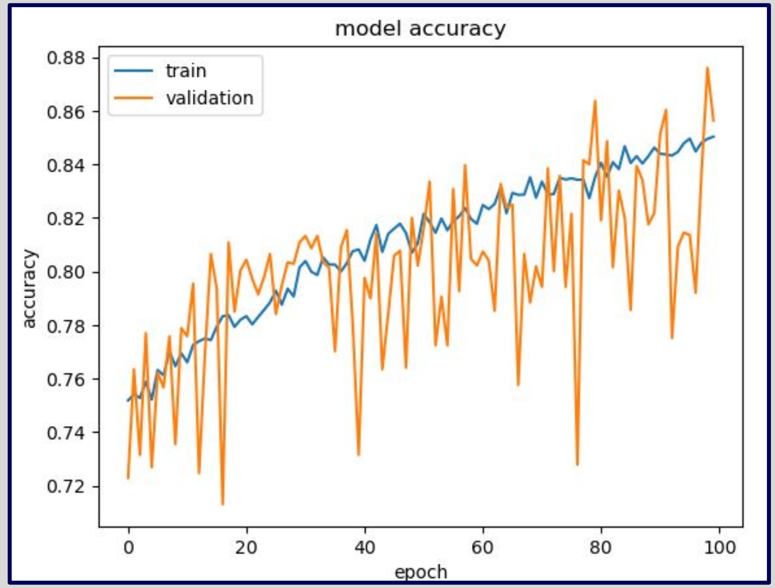

Fig 9.17: Tuned RCC_net model accuracy (task 2)

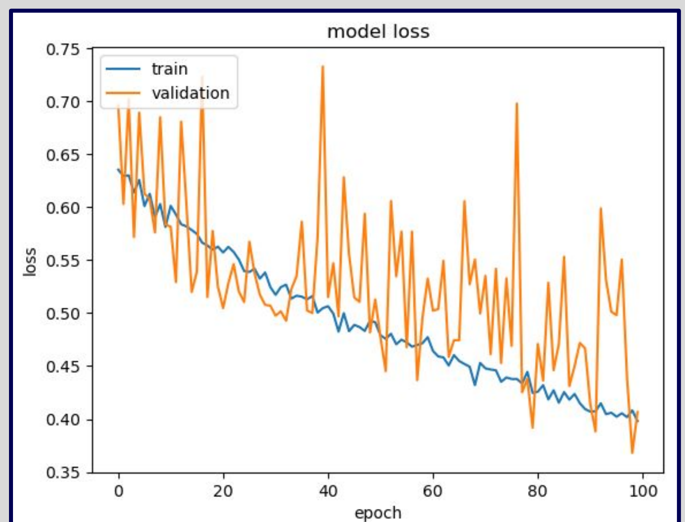

Fig 9.18: Tuned RCC_net model loss (task 2)

Ensemble Model

Task 1: Tuned Ensemble Model

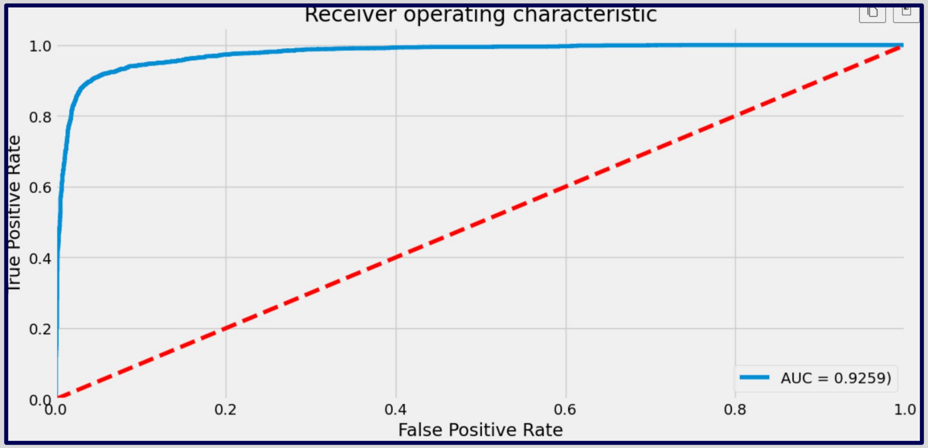

Fig 9.20: Tuned Ensemble ROC Curve (task 1)

Model accuracy for train set: 1.000
Model accuracy for test set: 0.926

	precision	recall	f1-score	support
0	0.94	0.91	0.92	3915
1	0.91	0.94	0.93	3915
accuracy			0.93	7830
macro avg	0.93	0.93	0.93	7830
weighted avg	0.93	0.93	0.93	7830

Fig 9.19: Tuned Ensemble accuracy score (task 1)

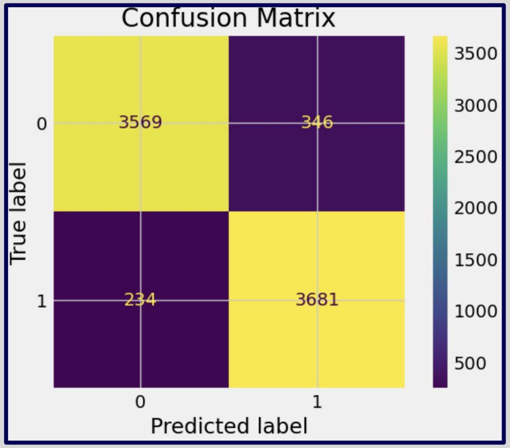

Fig 9.21: Tuned Ensemble model confusion matrix (task 1)

Ensemble Model

Task 2: Tuned Ensemble Model

```
Model accuracy for train set: 1.000
Model accuracy for test set: 0.911

              precision    recall  f1-score   support

           0       0.90      0.95      0.93      1219
           1       0.87      0.89      0.88      1219
           2       0.92      0.89      0.91      1219
           3       0.96      0.91      0.93      1219

    accuracy                           0.91      4876
   macro avg       0.91      0.91      0.91      4876
weighted avg       0.91      0.91      0.91      4876
```

Fig 9.22: Tuned Ensemble accuracy score (task 2)

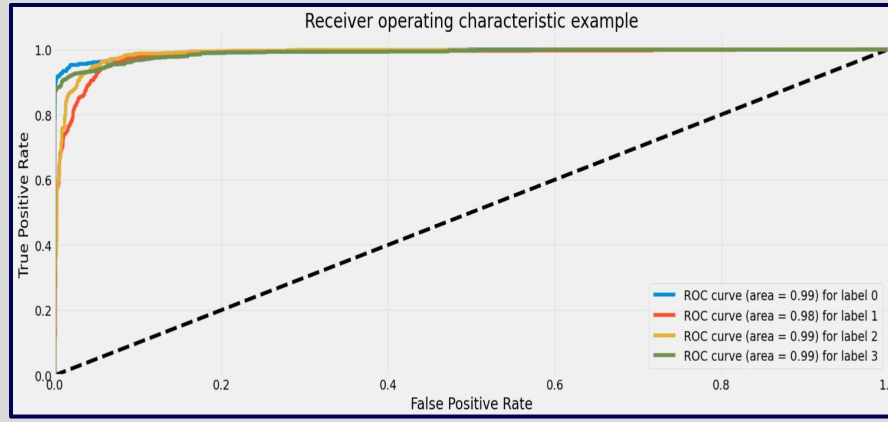

Fig 9.23: Tuned Ensemble ROC Curve (task 2)

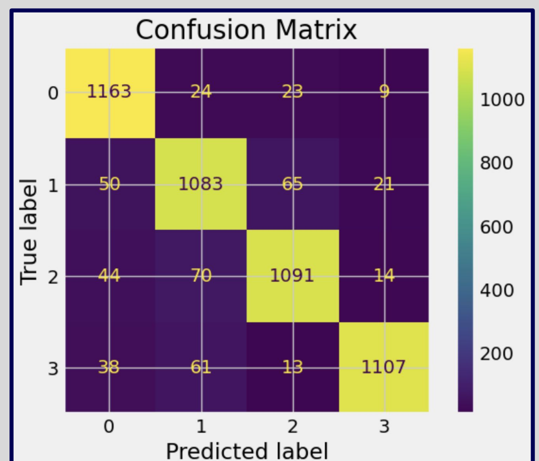

Fig 9.24: Tuned Ensemble model confusion matrix (task 2)

V. Discussion

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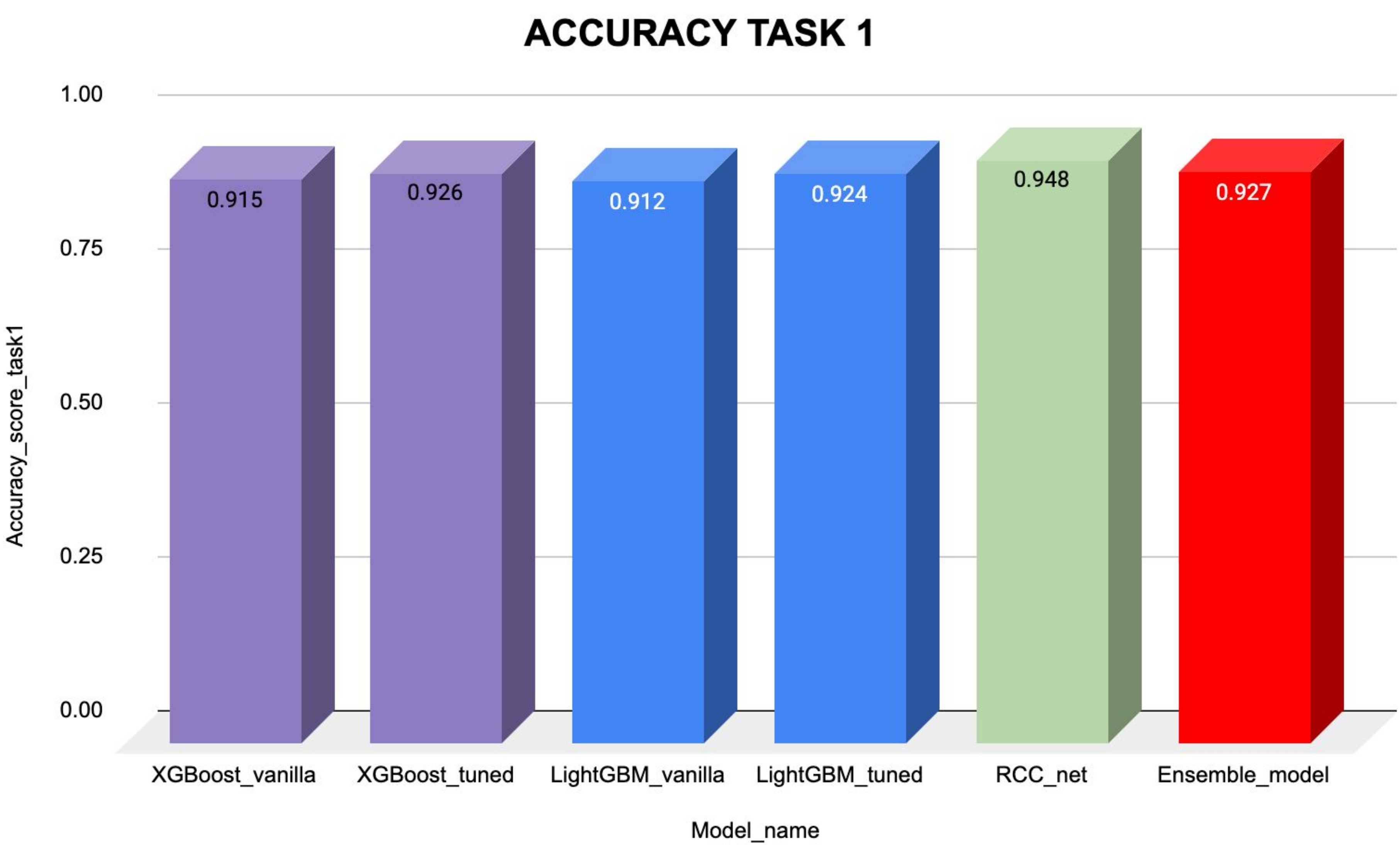
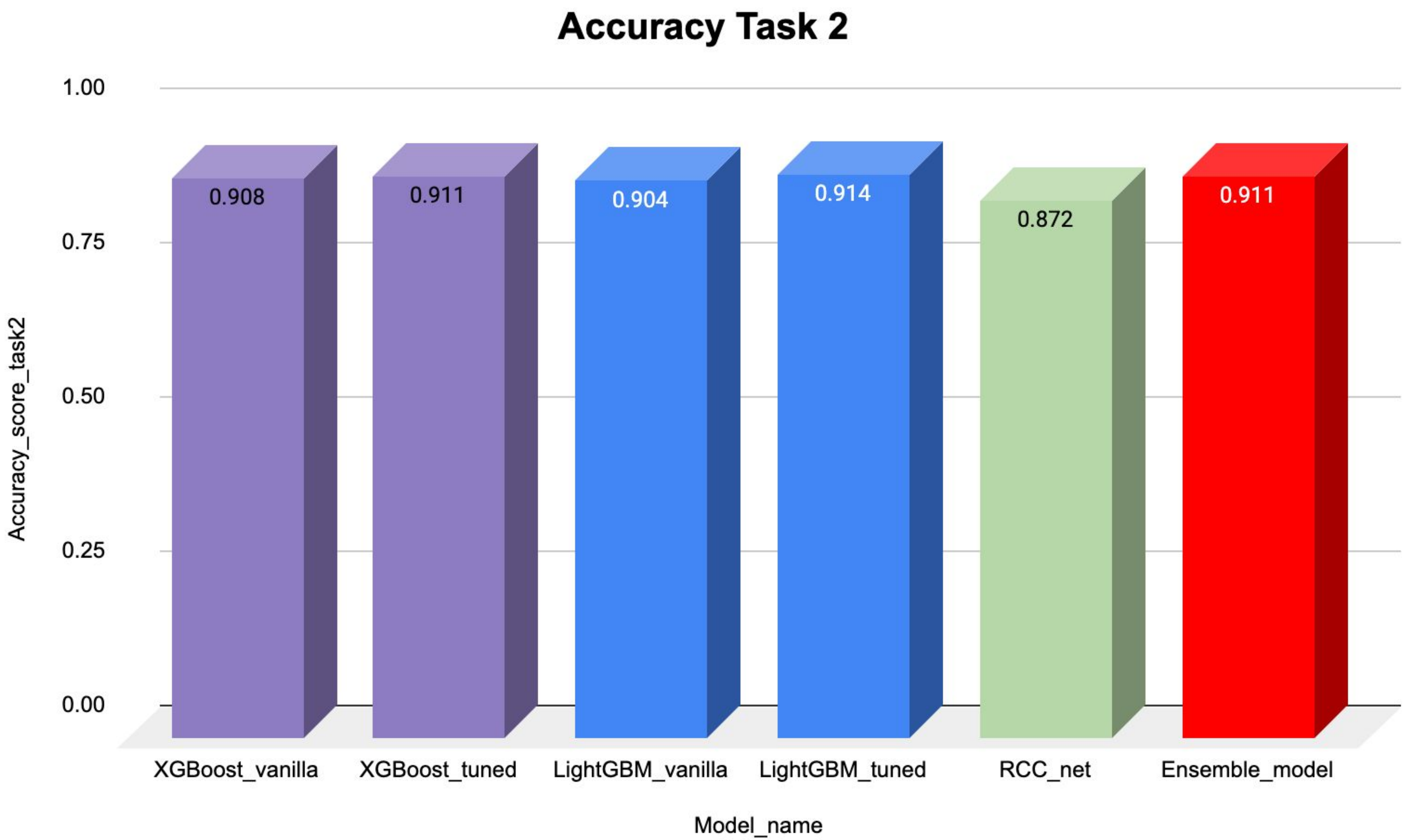
Result Model (Task 1)



Result Model (Task 2)



VI. Conclusion

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Conclusion

Best accuracy score for task 1: **RCC_net**

Score: 0.948

Best accuracy score for task 2: **LightGBM_tuned**

Score: 0.914

References

[1] World Cancer Research Fund International, “Worldwide cancer data: World cancer research fund international,” *WCRF International*, 14-Apr-2022. [Online]. Available: https://www.wcrf.org/cancer-trends/worldwide-cancer-data/. [Accessed: 17-Jan-2023].

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