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A LIGHTWEIGHT SHUFFLENET-V2 MODEL FOR MULTI-CLASS GASTRIC HISTOPATHOLOGY CLASSIFICATION WITH EXPLAINABLE AI

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Abstract

Gastric cancer is among the predominant causes of cancer-related death in the world that must be accurately and dependably examined by the histopathology. Proper interpretation of tissues is critical in early diagnosis in proper staging, and effective therapeutic decisions. Nevertheless, whole slide analysis using a manual method is tedious and subject to inter-rater error, whereas currently used deep learning systems tend to be computationally expensive and lack interpretability. The proposed paper uses a lightweight but a high-performing framework utilizing ShuffleNet-V2 to classify the gastric histopathology images into multi-classes. A subsample of 8000 histopathological image patches was taken out of a publicly accessible Kaggle dataset that comprises of 1000 samples of eight tissue classes. The proposed ShuffleNet-V2 with SE attention model was trained on dataset and compared with a number of pretrained models CNN, ResNet50, DenseNet201, EfficientNet-B3, MobileNet-V3 Large and Inception-V3 and identify best performing model. The proposed models were assessed in the different evaluation parameters. Also analyze the Mahalanobis distance, explainable AI and complemented by Mahalanobis distance. The model of ShuffleNet-V2 achieved an accuracy of 98.98. The ideal ROC and PR curves of the model are 99.90 and 99.90 respectively and high class-wise F1-score constantly, in comparison to all the other models. The explainable AI visualize the attribution maps that show the model to pay attention to the histologically significant structures, and favor meaningful clinical interpretability. The ultimate conclusion is that, ShuffleNet-V2 model is an accurate, efficient and explainable model to classify gastric tissue, and has high potential to be incorporated in the digital pathology process.

1.0 INTRODUCTION

Now a days gastric cancer (GC) is a serious concern of the population health in the global community and it has always been seen as one of the most frequently reported diseases in terms of morbidity and mortality. Though therapeutic agents have advanced to the healing of patients and to a great extent depends on the proper identification of the cancer at its early and precise stage [1]. The analysis of histopathological images of gastric tissue biopsies is the standard clinical practice that is used to identify early lesions, the various stages of tumours, and the affirmation of

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malignant lesions [2]. Pathologists need to view images of entire slides (WSI) in this analysis to identify subtle morphological changes, and multiple tissue characteristics and appearances. In an everyday practice, there is a increasing work load of diagnostics, lack of trained and experienced pathologists resulting in possible inability to conduct consistent and prompt assessments [3].

In order to deal with the challenges, need to come up with computer systems capable of assisting or improving on the diagnostic process. Traditional WSI analysis and interpretation is cumbersome and requires a lot of effort and is limited to a number of constraints. To begin with, scanning the rich histopathology image slides at high resolution implies the use of expert pathologists to study the thousands of image tiles that greatly adds time to the diagnostic procedure. Second, the results of diagnostics can vary among professionals because of the work experience, fatigue at work and subjectivity [4].

Thirdly, mild inflammatory changes in natural morphological characteristics of gastric tissue to atypical glandular formations complicate the classification of such a tissue among those, which are closely related tissues [5]. In order to deal with these problems, it must be able to provide high accuracy, rapid, and consistent automated computational methods of classifying tissues. Deep learning (DL) has proved to be an effective method of the medical image analysis in recent years, aimed at the detection and segmentation and classification of the gastric cancer. The convolutional neural networks (CNN) and hybrid model demonstrates strong capacity to acquire high-level health care representations through complex histopathological data without any need of hand engineered feature representation [6].

A number of studies applied the DL-driven method to the gastric histopathological images to derive the significant enhancement on the detection quality and lesion localization [7]. To make the process of transcending DL models between the research environment and clinical practice difficult. Most of the high-performance architectures like ResNet [8], DenseNet [9], and new transformer-based models require high computation capacities, heavy parameters, not to mention that they must be supported by special hardware in resource-intensive healthcare environments. The other is the issue of the model interpretability. To become widely used in clinics, pathologists should have a clue in which areas, morphological characteristics determine the choice of a model. In most of the older researches on DL, its investigation is performed as black boxes, and it does not present transparent, case-specific study. This absence of interpretability will create a question of accountability, trust and predisposed bias in that in case several types of tissues share similar histology structures [10].

Besides, categorizing the visually similar type of cancer tissue like stromal versus muscular bundles, and mucinous versus adipose Europeans presents a major challenge to current models which portrays incorrect classifications excepting in instance where strong feature-level separation is attained [11]. All of the above conversations reveal a gap in study that prompts the design of a deep learning model that is (i) efficiently computed, (ii) classifies more precisely on a variety of tissues of the stomach, (and), (iii) combines with efficient interpretability methodology. In order to remedy these, a lightweight model was proposed to categorize multi-class gastric histopathology image. ShuffleNet V2 is developed to enhance the precision that utilizes both channel splitting and depthwise convolutions to lower the computing expense.

The main goal of the research is to prepare a stable and computationally efficient DL model that will be able to accurately classify all eight histopathologic types of tissues to include adipose tissue (ADI), debris regions (DEB), lymphocyte-rich tissue (LYM), mucinous components (MUC), muscular tissue (MUS), normal epithelial structures (NOR), stromal tissue (STR), and tumor tissue (TUM). In order to fulfill objective, the study was based on a comprehensive evaluation method consisting of classical performance measures. Besides quantitative, much explainability analysis is conducted on Grad-CAM, Grad-CAM++, Eigen-CAM, and SHAP attribution maps to visually examine the process of decision-making by the model and ensure its consistency with significant histological structures.

Moreover, the paper has integrated the Mahalanobis distance-based outlier detection on a low-dimensional PCA space to investigate feature embedding stability and detecting possible anomalies in the tissue group. This additional analysis gives the derived model sufficient strength to not be dependent on any spurious correlations and give it strength within the dataset.

The most important findings of the paper are as follows: To explore the gastric histopathology classification model (which allows quick inference and minimal computation costs) of high efficiency.

Grad-CAM, Grad-CAM++, Eigen-CAM, and SHAP are some of the simplest interpretability techniques incorporated to offer class specific explanations on why the model predicts certain things in a transparent and understandable manner.

Strength testing based on Mahalanobis outlier detection indicating the stability of acquired feature embedded and cases that have both unclear morphological features.

According to Xia et al. (2025), the histological classification reported by the authors had a high realization of accuracy more than 95.00 percent, which demonstrates CNN as a useful diagnostic model in spite of current limitations associated with small-scale training and external validation information [12]. On the same note, Gul et al. (2024) achieved the accuracy of 90.00 per cent and the high specificity of 92 per cent of lesion in the early stages compared to the unidentified data in the endoscopic image over the DL model. Newer studies have proven to be on hybrid model and optimization-based [13].

Bilateral filtering, CapsNet, snake optimization and a deep belief network were proposed as part of the SOADL-GCC model by Almarshad et al. that achieved 99.72 percent accuracy on the Kvasir dataset [14]. Ucak carried the transformer-based multi-stage model to categorize the histopathological images that integrate the feature selection as particle swarm optimization and achieved the 97.96% detection precision [15]. Attention based model is more interpretable and stable in classification. Accuracy score of 98.00 percent of the multi-channel attention mechanism according to the multi-class gastric histopathology datasets was achieved by the author Zubair et al. (2024) [16]. In the same way, a hybrid architecture GoogLeNet-ViT with Faster R-CNN segmentation was proposed by Ul Haq et al. (2024) with classification accuracy of 97.4 percent and strong sensitivity (97.5) [17].

Multi-class lesion differentiation Clinical grade DL solutions have also been suggested [18]. According to Kim et al. (2024), a six-class CNN model was created that is capable of detecting per-patient lesions with an overall rate of more than 95 per cent including 100 per cent early gastric cancer. The hybrid model that considers a combination of the various DL models including LSTM, GRU and CNN are also employed to detect and classify the GC [19]. To achieve the 98.5 percent accuracy [20], Kalimuthu et al. (2024) suggested a dual-stage Bi-LSTM model as a progression of obtaining it.

According to another study by Wang et al. (2025), the CNN-GRU fusion model is placed on the hyperspectral data thus getting the AUC of 0.86 [21]. Bhardwaj et al. (2024) achieved a high level of performance on different types of gastric categories with the EfficientNetB6 model to achieve the 99.88% accuracy. Subedi et al. (2024) used a CNN-Transformer hybrid to sport the MCC of 0.8191 on Gastro Vision dataset and Kvasir-Capsule [22] in the field of gastrointestinal abnormality detection [23]. There is also another study, which demonstrates the significance of dataset balancing [24, 25].

The imbalance of the classes choosing the cases in cancer make the cases less sensitive and on the other hand, the learning is cost-sensitive is a requirement in real life situations [26]. The literature above reveals the hybrid DL model, attention mechanisms, transformer models, and optimization-driven models that are evidently the most promising in comparison with the traditional CNN models [27, 28]. Yet, there are still holes in terms of diversity of the datasets, generalization, interpretability, as well as, standardized evaluation.

2.0 METHODOLOGY

The model that was proposed to the structured model and then combined with computationally efficient model was used to identify and classify the gastric cancer over the histopathological images as presented in Figure 1. Firstly it takes data in pubalically obtainable source and then pre processing it with scaling and normalizing to create an even intensity distribution and steady convergence during training. To maintain the diversity of classes and minimize sampling bias the K-means clustering is used before the partition of the dataset. Several CNN pretrained models (ShuffleNet-V2, ResNet50, MobileNet-V3 Large, CNN, Inception-V3, EfficientNet-B3, and DenseNet201) are trained under the same experimental conditions in order to compare them equally. Test results of model suggested with various evaluation criteria. Lastly, SHAP explanations to interpretability to reveal the discriminative image areas to aid clinically transparent decision-making. This is the general framework of the intended model in all the phases of analysis depicted in figure 1.

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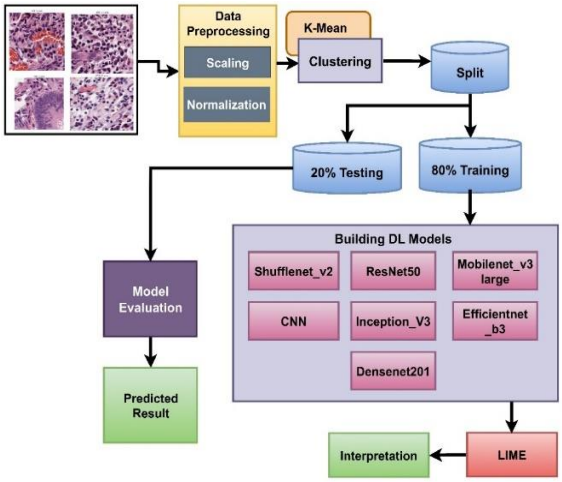

Figure 1: Block diagram of proposed model

Dataset description: This paper used a publicly available histopathological gastrin cancer dataset that are available at Kaggle including 31,000 image patches scraped out of 300 whole-slide images. The data is high-quality curated annotations of eight tissue types of interest that fill a longstanding gap in the provision of large and high-quality histological data of gastric cancer. To achieve consistent representation of all tissue types in this work, a balanced sample of 1000 images of each class was applied as well as to compare the models without any bias effects. The random distribution of the images into 80 percent training, 10 percent validation, and 10 percent was to ensure even distribution throughout all the classes. This trained and curated and class balanced data will help to train powerful models, achieve equitable evaluation, and reproduce match experimental results.

3.0 RESULTS AND DISCUSSION

All images with histopathological gastric cancer were resized to 224 x 224 pixels so that the input size across varying imaging conditions was similar. The Min-Max normalization was used to maximize the pixel intensity values with the range [0,1] which will not alter the contrast of the image but will avoid the overexposure effect.

$$I_{normalized}(x,y) = \frac{I(x,y) - I_{min}}{I_{max} - I_{min}} \quad (1)$$

In which, I(x,y) is actual pixel intensity of location(x,y), I max and I min is the minimum and maximum intensity of input images.

Figure 2 represents the class-wise representation of the histological gastric cancer data set which demonstrate that all the eight 1,000 images were the same (STR, DEB, LYM, MUS, NOR, MUC, TUM, and ADI).

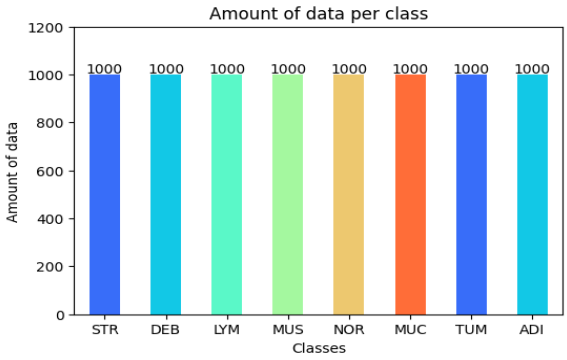

Figure 2: Distribution of the dataset

This balanced distribution demonstrates that the dataset is even and eliminates the chances of bias caused by imbalance of classes and the model ends up getting equal representation of the each type of tissue in the training. This equalized pattern aids in equitable learning, levels off the gradient update, as well as increases the dependability of comparative performance assessment across courses. Sample Images of Dataset is mentioned in the figure 3.

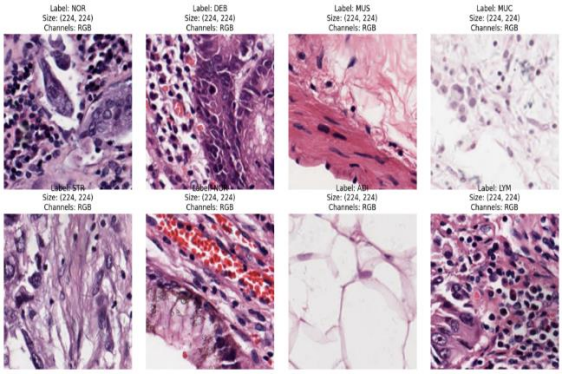

Figure 3: Sample images of dataset

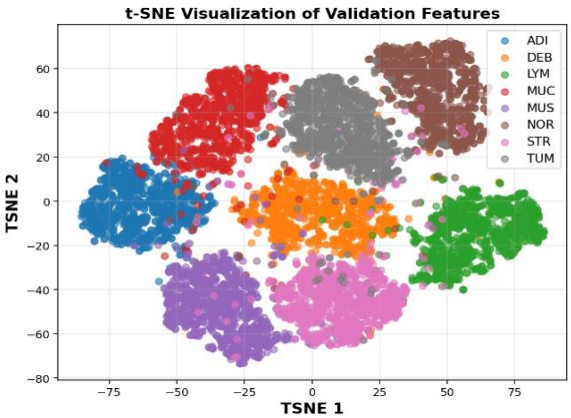

Figure 4: The samples of representative histological images of each of the classes of gastric cancer dataset are depicted

Figure 4 show the images of distinct morphological features related with different tissue types, Figure 4 present the images of various morphological characteristics associated with the various types of tissue, such as NOR, LYM, MUC, MUS,STR, DEB, TUM and ADI. It means every cellular pattern displaying the data diversity in each site proves the tissue classes and how a particular data type requires the development of discriminative features during the training of the suggested DL models.

ShuffleNet-V2 model will be used in this research as it is optimized on the channel split, efficacy on pointwise convolution and much less number of parameters which allow to conduct rapid inferences of large-scale histopathology images. The model is not heavy that renders it simple to deploy the resources on clinical hardware that do not undermine the representational strength. ShuffleNet-V2 was trained with 50 epochs based on the optimization strategy that is aimed at providing the stable convergence and strong generalization of all 8 types of gastric tissues and minimizes the problem of overfitting. The 1x10-4 learning rate Adam optimizer used to update the adaptive gradient and effective management of sparse gradient that manifests in the case of histopathological features extraction [26].

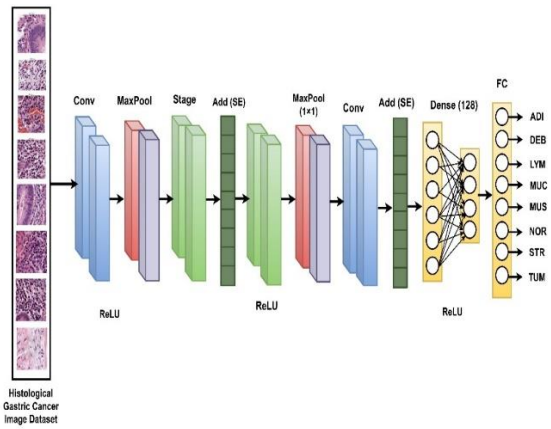

Figure 5: Architecture of shufflenet-V2 model

Figure 5 displays the architectural architecture of ShuffleNet-V2 model in order to detect and classify the gastric cancer cancer in the histopathology images. The images that are processed through an initial convolution and max-pooling process, and then a series of ShuffleNet-V2 operations with channel splitting and efficient feature mixing are used. Attention was developed to squeezeandexcitation (SE) attention added in afterstage steps to optimize channelwise features recalibration in order to make the distinction of subtle tissue features. The next block of max- Pooling and convolutional block improve the spatial and semantic representation. The denoised deep features are inputted into the dense final layer of 128 neurons with ReLU and lastly into a fully connected output layer resulting in class probabilities of the eight tissue classes. The model focuses on computational efficiency, lightweight extraction features and increased representational capacity in stages that have been enhanced with SE. The model is lightweight with greater channel attention that demonstrates the better performance.

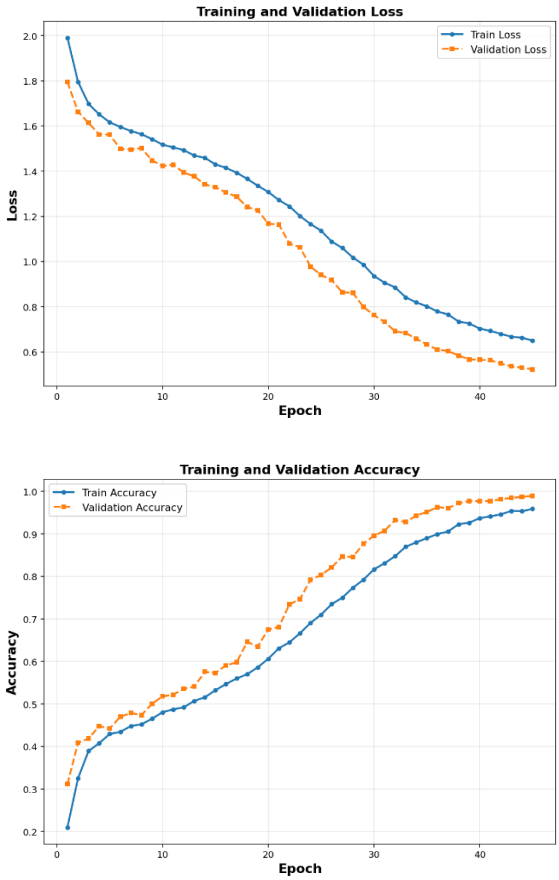

Figure 6: Training and validation accuracy of shufflenet-V2 model

The training and validation curves of the ShuffleNet_ V2 model presented in figure 6 depict stable and successive increase in learning of the model per epoch. The training and validation loss also decreases steadily showing the successful optimization devoid of overfitting. The validation loss is a bit lower than the training loss during the period of training which imply the good generalization ability. The accuracy curves depict the consistent rising trend with the validation accuracy steadily performing excellently in comparison to the training accuracy that demonstrate the almost perfect classification accuracy.

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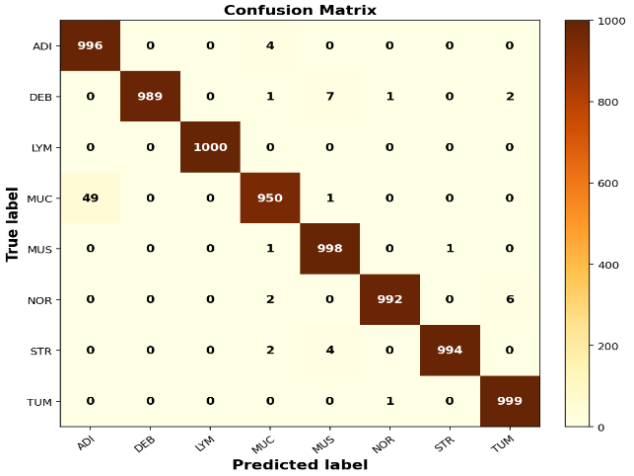

Figure 7: Confusion matrix of the shufflenet-V2 model

Figure 7 indicates the confusion matrix of the ShuffleNet_V2 model with the results of the correct performance of the multi-class for all eight histological gastric tissue classes. The near-perfect prediction of ADI (996/1000), DEB (989/1000), LYM (1000/1000), MUS (998/1000), STR (994/1000), and TUM (999/1000) correctly identified with minor misclassification is seen across most of the classes. NOR class has a good performance with 992 hits and few cases of confusing with ADI (2 samples) and TUM (6 samples). The highest misclassification rate is reported in MUC class where 49 samples were mistakenly identified as ADI and 1 sample as MUS which also had the highest number of correct predictions that was 950.

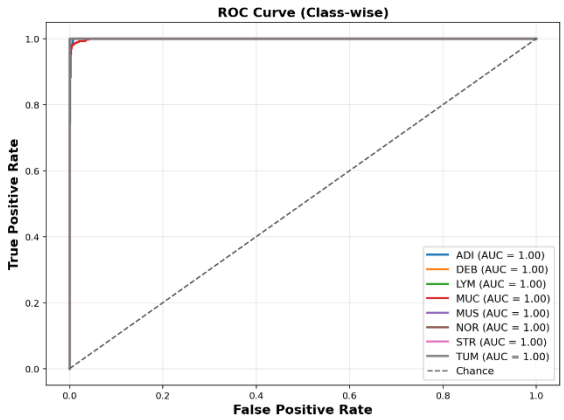

Figure 8: Class-wise ROC–AUC curves of the shufflenet-V2 model

Figure 8 presents the curves of the ROC-AUC classes of the ShuffleNet_v2 model across all eight classes of the histological gastric tissue. All curves are further filled in the upper-left corner and every class has the AUC of 1.00 that signify excellent discrimination between positive and negative samples across all decision thresholds. This performance fits the puzzlement table, with majority of the classes including LYM, TUM, STR, MUS having 998-1000 correct predictions on 1000 samples and only several misclassifications are seen (e.g., there is no longer confusion between MUC and ADI). The ROCs thus validate the fact that the model has a very high true-positive rate with nearly non existent false-positive rate in all the gastrointestinal tissue groups and indicates great ranking ability and high separability between the learned feature presentations of all gastrointestinal tissue types.

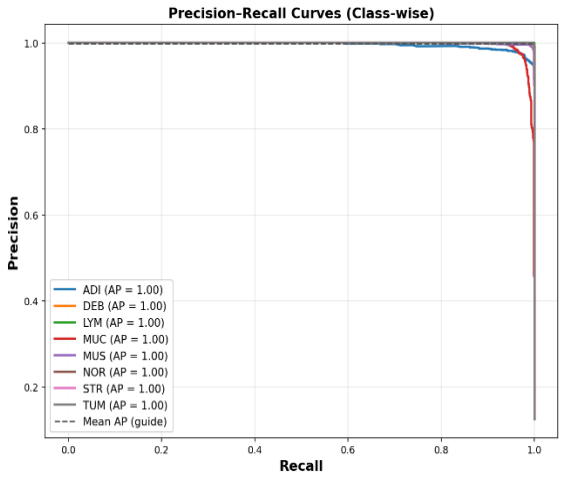

Figure 9: Precision–Recall curves for the shufflemet-V2 model

Figure 9 depicts the PR curves in the class-wise mode of the ShuffleNet_v2 model represent steady high precision and recalls throughout all the eight histological gastric tissue classes, with a per individual class recording an average precision (AP) of 1.00. The curves are closely focused in the upper-right section that signifies that the model maintains its close to perfect accuracy at the extreme levels of recall as well. Most of the classes like LYM (1000 correct), TUM (999 correct), MUS (998 correct), and STR (994 correct) indicate the least misclassification.

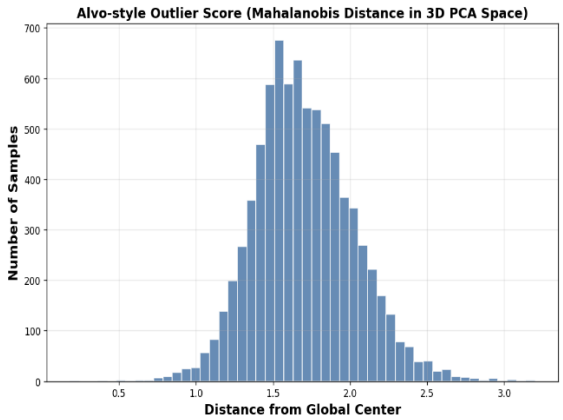

Figure 10: Distribution of Mahalanobis distance-based outlier scores of ShuffleNet_v2 in 3D PCA space

The distribution of Alvo-style outlier scores calculated based on Mahalanobis distance in a 3D PCA feature space of ShuffleNet_v2 model is presented in Figure 10. The histogram reveals the near-normal distribution centered around the distance of around 1.4-1.7 which demonstrates that most of the samples are clustered and most part of the feature embed is close to the global data manifold.

4.0 CONCLUSION

This paper proposed a ShuffleNet-v2 based DL model to tell and categorize the gastric cancer on gastric histopathology images. The model shows the excellent predictive power that has achieved the accuracy of 98.98 percent and always large values of predictions recalls and ROC–AUC in all the classes. It was confirmed in confusions matrix and outlier analysis that there was a high degree of generalization, explainability methods as Grad-CAM, Eigen-CAM, and SHAP proved that the model learned biologically relevant morphological cues. Due to lightweight design and high-performance computing, ShuffleNet-V2 model demonstrates the scalable approach to the digital pathology workflow and has a possibility to promote the quick, reproducible, and explainable clinical decision-making.

The next step in the future should be testing the proposed model on multi-center and large-scale whole-slide image datasets in order to guarantee clinical viability in different populations and scanning settings. Multimodal data (e.g. genomic markers, patient metadata or radiological imaging) could be further integrated to increase the accuracy of the diagnostic results. Self-supervised exploration online pretraining and transformer feature hybrid models can be enhanced. Also, the uncertainty estimation and the implementation of the framework in practice at the diagnostic environment will make it more beneficial as a guide to the pathologists.

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