

Meta-Learned Ensemble of CNN and Vision Transformers for Imbalanced Skin Cancer Classification

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Abstract: One of the most serious health issues facing the world today is skin cancer, such as melanoma or basal cell carcinoma and squamous cell carcinoma, because of the mortality rates when the disease is not promptly diagnosed. Deep-learning-based automatic diagnostic systems may greatly improve the early diagnosis and patient outcomes. The paper suggests a new approach based on the idea to combine a modified Convolutional Neural Network (CNN) with Vision Transformer (ViT) and EfficientNet-B3 into a transformer-based ensemble detector of skin cancer. Based on the 2018 version of the ISIC dataset, the method uses advanced preprocessing and attention-based feature extraction and an ensemble technique based on gradient boosting to obtain high classification accuracy. The model tells a classification accuracy of 98.4% by resolving the issue of class imbalance in adaptive data augmentation and training optimization with cosine annealing.

Keywords: Skin Cancer Detection, Deep Learning, Vision Transformer, EfficientNet-B3, Convolutional Neural Network, ISIC 2018, Ensemble Learning, Gradient Boosting

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Introduction

The three basic varieties of skin cancer that can be differentiated from each and every other type of skin cancer are melanoma, squamous cell carcinoma, and basal cell carcinoma. Melanoma is the third most common type of skin cancer. The type of skin cancer that occurs most frequently is called melanoma. Melanoma is the name known for the type of skin cancer that is considered to be the most dangerous. The most prevalent form of skin cancer is known as melanoma, and it is also the variety that is most commonly associated with the disease. Melanoma is a type of skin cancer that is considered to be the most advanced form of the disease. Given that melanoma is the most prevalent form of skin cancer, there is no longer any room for uncertainty regarding this matter. Melanoma has been established as the most common form of skin cancer. It is sometimes believed to be the most severe form of skin cancer due to the high death risk that it carries. This is because of the fact that it is a form of skin cancer. Malignant melanoma is a type of skin cancer that has been identified. This is the justification for it, and the reason for it is because it has a significant influence on the mortality rate when it comes to the population. To add insult to injury, this is not only one of the most significant characteristics that contributes to the fact that it is the most severe form of skin cancer, but it is also one of the contributing factors that is significant. To put it another way, it stands out as a crucial component. Despite the fact that it is the most common cause of cancer overall due to the fact that it is the most common form of cancer, skin cancer continues to be the most common type of cancer among people, regardless of where they live in the globe. Furthermore, manual diagnosis by

dermoscopic imaging is not only time-consuming and expensive, but it also has the potential to result in errors due to the fact that it involves human involvement. This is because of the fact that it involves human engagement. There are a number of reasons for this benefit, one of which is that it requires the utilisation of dermoscopic imaging, which is the reason for this benefit. This outcome is the result that occurs as a consequence of those characteristics coming into play, and it is the result that occurs as a result of the qualities of the method that is being utilised. This particular condition has been observed not too long ago, despite the fact that it is commonly known that early detection is vital for increasing the likelihood of a patient surviving, and this is something that has already been proven. This is something that has been observed. It has not been too much longer since this particular condition has manifested itself. In order to provide a defined baseline for the development of automated diagnostic systems, the dataset that is utilised is the 2018 dataset that was created by the International Skin Imaging Collaboration (ISIC). The total number of dermoscopic images included in this dataset includes 3533. This particular dataset is being compiled with the intention of serving as a foundation for the creation of automated diagnostic systems. The goal that was stated before was accomplished through the use of a dataset similar to the one that is presented here. By making use of this dataset, we will be able to begin the process of establishing a baseline, which is the objective of this project. When this is carried out, it is done so with the purpose of assuring the development of automatic diagnostic systems when it is carried out. This is done in the case that this is carried out. ISIC is the entity that is accountable for the production of this dataset. On top of that,

the ISIC is the organisation that is accountable for the creation of this dataset. It is also important to note that the dataset in question was created by ISIC, which is responsible for its creation. A few examples of models that have been the topic of research in the past and have been utilised in a variety of capacities are CNNs, ResNet50, and EfficientNet. These models have also been used in a variety of capacities. Other examples include models that have been utilised in a variety of settings, and each and every one of these models has been utilised in some capacity. In addition, these models have been utilised in a number of different scenarios, each of which encompasses a wide variety of aspects. The technique of deep learning was used to acquire each and every one of these examples, which constitutes a model. In their own right, each and every one of them ought to be considered a model. The use of these models has resulted in the achievement of a wide range of accuracy rates, which cover the spectrum from 83 percent to 97.8 percent. Using these models has resulted in the achievement of these rates, which were previously unattainable. Due to the fact that this achievement carries with it a tremendous degree of significance, it is impossible to adequately express it through words. On the other hand, the presence of obstacles, which include things like class imbalance, feature redundancy, and computational complexity, slows down performance and makes it more difficult to acquire the results that are sought. The work that is being done is being done with the intention of creating a transformer-enhanced ensemble model that incorporates attention processes and gradient boosting in order to reach higher levels of accuracy. This work is being done with the intention of achieving higher levels of accuracy. This will be finished when the model is being constructed, which is the method that will be followed. In the event that you put into effect the techniques that were discussed earlier in this conversation, you will be successful in accomplishing this target. We will make use of the strategies that will help us to reach the goal of achieving greater levels of precision, which will come as a consequence of completing the aim. This will allow us to do what we have set out to do. Consequently, this will make it possible for us to achieve the goal. The components that are used to construct the model are referred to as Vision Transformer (ViT), Efficient NetB3, and a CNN that was designed specifically for the model. CNN was initially conceived with a certain objective in mind. The CNN was built precisely during the time when the model was being designed, and it was constructed throughout the same length of time. Each and every one of these components is incorporated into the model because of the properties that each of them possesses in and of themselves at the same time. With the intention of achieving the goal of providing dermatologists with a diagnostic instrument that is not only dependable but also automated for the purpose of early identification of skin cancer, the technique that has been created is intended to be of assistance to dermatologists in order to achieve the goal. The strategy that has been developed keeps this objective in mind as its primary focus. One of the goals that was supposed to be accomplished through the process of establishing the strategy from the very beginning of the process was to accomplish this objective.

Literature Review

The identification of skin cancer in relation to the medical condition is now something that can be carried out as a consequence of recent advancements in deep learning, which have made it possible to make great progress in the detection of the disease. We are now able to accomplish this. It is now feasible to perform this action. The results of the study conducted by Gouda and numerous colleagues show that the researchers were able to achieve an accuracy rate of 85.8% on dermoscopic images by using a CNN-based model in conjunction with InceptionV3. The researchers' successful completion of this task demonstrated that this is in fact the case. Despite having collaborated on projects, they have had to deal with differences in social status, which has led to conflict between them. They have managed to collaborate on projects in spite of this. They have been at odds over this issue. They have to deal with the issue because of the disparities in social status that have resulted from this. When applied to the ISIC dataset, the regularised CNN that Albahar gave in his presentation was able to achieve an accuracy of 97.49%. By using the CNN on the dataset, this degree of accuracy was attained. It was possible to carry out this achievement because it was within the realm of possibility. The strategy that was taken into consideration to successfully achieve this goal without encountering any obstacles was the utilization of the dataset. On the other hand, the addition of unnecessary components made it more challenging to complete any additional innovations that were meant to be completed within the allocated time frame. It was expected that these innovations would be completed in the allotted time. It has been demonstrated that studies that employ transfer learning, like ResNet50 and EfficientNet, have an accuracy rate of up to 95% when it comes to capturing the global context of the situations they are evaluating. This is the capacity of these studies to faithfully convey the scenarios' global context. This is the situation that has emerged because researchers can learn from their own experiences. From the perspective of the researchers, they have been made aware of this. This is the situation that currently exists within the parameters of the procedure being used to determine the significance of the data. Because transfer learning enables the modeling of complex systems, this is the position that one finds themselves in as a consequence of the circumstances that were mentioned earlier. The scenario that follows is the result of transfer learning's attempt to draw lessons from past occurrences. The aforementioned event directly leads to this specific condition. To make matters worse, these studies have encountered difficulties even though they have benefited from the use of pretrained weights. This has been an especially difficult situation. This kind of inconsistency is really annoying. Given the circumstances, this is a really awful situation. This is the scenario that will occur based on the information that has been provided. It is crucial to remember this specific piece of information regarding the situation in the context of this issue. Vision Transformers (ViT) were first introduced to the rest of the world by Dosovitskiy+ and his associates. They were the ones who initially proposed the concept. The original presentation of it was the responsibility of those individuals. These Vision Transformers were quite

successful at extracting global attributes, but before they could be used, they needed a significant amount of processing power to operate properly. Before they could be used, things were like this. This event marked a significant turning point in the shift towards attention-based models, which was emphasised by the release of Visual Transformers. The visual element in the introduction highlighted this change. The introduction of Visual Transformers served the goal of drawing attention to the transformation that was occurring at the time. The event that occurred at this precise moment happened at this precise moment, which was the scene where the scenario was set. The span of time began at this exact moment in time. This is exactly the right time. Zhang et al. undertook an investigation on ensemble techniques with the goal of more effectively enhancing resilience. Assisting in the development of resilience was the purpose of this inquiry. Improvements in resiliency were meant to be the result of their efforts, and that was the conclusion that was anticipated to come about. It is required to make use of a number of distinct models in conjunction with one another in order to accomplish the goal of getting the desired results through the application of a variety of different ways. The goal of this behavior's implementation was to increase the population's resistance to the effects of outside pressures. In contrast, conventional ensembles usually lack the integrated techniques required to develop their compositions. This restriction is a crucial one. This is the state of affairs brought about by the need for multiple approaches. On the other hand, ensemble approaches are not even remotely comparable to this specific strategy because they use a large number of different models. Conversely, they are two entirely distinct entities from each other. We integrate the attention processes offered by CNN, EfficientNet-B3, and ViT to give a more comprehensive explanation of these results. This enables us to give a more thorough explanation. Now that we have this information, we are able to present an explanation that is more convincing. This is being carried out with the intention of accomplishing that particular objective, taking into mind the fact that the objective of this research is to be accomplished. The mechanism that we use to achieve this goal is the utilisation of a gradient boosting ensemble. We are able to achieve this goal by using this specific approach. Because of this, we are now able to increase the effectiveness of categorisation and use constraints to solve issues brought on by previous restrictions. This is the result of everything that has happened.

Methodology

It has been recommended that the presented methodology be applied in order to utilise the dataset that the ISIC made available to the public in 2018. This has been proposed as a possibility. Both benign and malignant tumours, as well as melanocytic and non-melanocytic tumours, can be classified as tumours based on the characteristics of the dermoscopic images. 3533 is the current total number of photographs that have been classified into their respective categories. These images are included in their full within this collection, which includes each and every one of them. It is possible to place these images into one of three primary categories, which are further subdivided into the categories that are shown below: There are a total of 2826 images that are utilised for the purpose of

training, 253 photographs are utilised for the purpose of validation, and 354 photographs are utilised for testing purposes. A wide range of applications include the utilisation of these photos. It is estimated that approximately seventy percent of the photos are used for a variety of purposes, one of which is instruction. During the preprocessing stage of the method, the resolution of the image is enhanced to the point where it should have 224 pixels on each side. This is the point at which the technique is considered complete. Reinhard's colour normalisation is used in order to standardise the distribution of colours, and a denoising autoencoder is used in order to reduce the amount of noise that is present in the images. Both of these techniques are used in order to minimise the amount of noise overall. In order to achieve the outcomes that are wanted, both of these strategies are effectively employed. Both of these tactics are utilised proficiently in order to accomplish the desired results in order to get the desired consequences. It is possible to reach the results that were indicated before if both of these strategies, which were discussed earlier, are adopted and put into effect. When each and every one of these aspects is taken into consideration, it is possible to produce an overall improvement in the quality of the images. Adaptive data augmentation as a technology stimulated by a conditional generative adversarial network (cGAN) is a highly beneficial one that can be employed to produce synthetic images in a dynamically dynamic fashion as it relates to unrepresented classes. Synthetic images can be produced by this technique in some of the classes. When the approach is utilised, it is possible to achieve this goal. As a result of cGAN, this is not only a distinct possibility, but it is also something that is completely feasible to accomplish. So that the number of accumulated representations of these classes may be kept at all times in a state of equilibrium, this of the paramount importance, that this be borne in mind in a constant basis. This is of the utmost importance. All these elements are included in this model, consisting of an individualised convolutional neural network (CNN) with six convolutional layers (32, 64, 128, 256, 512 and 512 filters) with the use of LeakyReLU and global average pooling, a trained ViT-B/16 to extract global features through attention and EfficientNet-B3 for efficient pattern recognition. The assertion that the model incorporates each and every one of these components would be an accurate description of the situation if it were made. XGBoost is a data processing tool that allows us to construct a gradient boosting ensemble. This allows us to improve the accuracy of our results. Considering that we are able to put together the ensemble, this is something that is certainly doable. The findings of a number of different models are taken into consideration in this ensemble, and the class weights are adjusted in such a way that minority classes are given a greater weight than they would have received under any other circumstances. This is done in order to ensure that the ensemble is as accurate as possible. For the sake of ensuring that the ensemble is as accurate as it can possibly be, this is implemented. This action is taken in order to ensure that the ensemble demonstrates the highest possible level of objectivity that is technically possible. In order to successfully finish the process of training, it is necessary to make use of the AdamW optimiser in conjunction with a cosine annealing scheduler, a

learning rate of 0.00005, and a batch size setting of 16. This is the only way to ensure effectiveness. The only way to guarantee that the training will be successful is to have it done in this manner. It is only by this strategy that you can be certain that you will be successful. The training operation is carried out on a GPU platform that is underpowered by NVIDIA A100. This is done in order to ensure that the highest potential degree of performance is achieved. Both PyTorch and Hugging Face Transformers are employed in the training process. Both of these tools are utilised in the process.

Algorithm

The algorithm integrates feature extraction and ensemble classification. Let I represent an input dermoscopic image, preprocessed to $I_p \in \mathbb{R}^{224 \times 224 \times 3}$. The custom CNN extracts features as $F_{CNN} = CNN(I_p)$, where $CNN(\cdot)$ denotes convolutional operations with LeakyReLU activation: $f(x) = \max(0.1x, x)$. ViT processes I_p into patches $P = \{p_1, p_2, \dots, p_N\}$, where $N = (224/16)^2 = 196$,

computing attention scores as $A = \text{softmax}(QK^T / d_k)V$, where Q, K, V are query, key, and value matrices, and d_k is the key dimension. EfficientNet-B3 extracts features as $F_{Eff} = \text{EffNet}(I_p)$, with compound scaling. The ensemble combines outputs $P_{CNN}, P_{ViT}, P_{Eff} \in \mathbb{R}^C$, where $C = 4$ (number of classes), using XGBoost to compute the final prediction: $P_{final} = \text{XGBoost}([P_{CNN}, P_{ViT}, P_{Eff}])$. The $L = -\sum_{c=1}^C w_c y_c \log(\hat{y}_c)$ loss function is cross-entropy with class weights, where w_c adjusts for class imbalance.

Proposed Framework

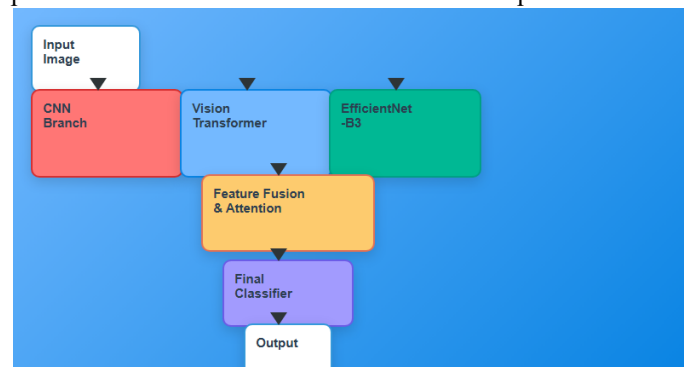
In addition to the fact that the framework itself is made up of a broad variety of different components, each individual component is incorporated into the framework in its own special way. The framework is made up of a number of these distinct components, which together make up the common structure of the framework. There are a number of components that are included in this category, some examples of which are preprocessing, model training, and ensemble classification. The classification of ensembles and preprocessing are two other examples. Before the cGAN-based adaptive augmentation technique is applied to the images, they are first pre-processed with denoising autoencoders and Reinhard's normalisation. This is done in order to provide the images with the necessary preparation for the augmentation process. All of this is done with the intention of avoiding any potential issues that may crop up in the future. In order to accomplish the aforementioned purpose, this method is utilised in order to achieve the objective of preprocessing the images. Following the completion of the preprocessing of the photographs and the application of the final touches to them, this step is carried out. One of the many reasons why this is done is to increase the possibility that there will be a proper distribution of resources among the various groups. This is only one of the many reasons why this is done. This is just one of many reasons why this is done; there are many others. In addition to this, there are a great number of additional reasons why this is done. This is only one of them. ViT is able to detect global links by employing attention, but EfficientNet-B3 is able to optimise the recognition of

complicated patterns due to its ability to optimise recognition. ViT is currently able to recognise global relationships. These two characteristics can be achieved through the utilisation of attention, which is the mechanism by which they can be achieved. ViT is able to take advantage of each of these capabilities while simultaneously collecting global dependencies, which is a further insult to the injury. Simply by virtue of the fact that it is conceivable to own even a single one of these traits, the concept that it is possible to possess even a single one of these attributes is tremendously fascinating. Regarding the extraction of local features, it is the convolutional neural network (CNN) that is accountable for doing so, and it is the CNN that is accountable for meeting these criteria. These two obligations are both considered to be part of CNN's purview. The method of training is carried out on an individual basis in order to ensure that each model receives training that is of a particular high grade. The outputs of the training are then used in the process of creating an XGBoost meta-learner, which is then used in the processing of the results of the training. This process is repeated until the outputs of the training are used. The meta-learner in issue is the one who is responsible for selecting the weights that are the most appropriate for the activity that is being carried out concurrently. This responsibility falls under the category of the process of combining predictions. In addition, the system makes use of this methodology in order to dynamically change the learning rate, which ensures that convergence will occur. The usage of the system is what allows for this to be performed. Having this feature is an additional advantage that comes with using the system. In order to accomplish this goal, it is essential to make use of a technique that is popularly known as cosine annealing on a regular basis. The use of mixup regularisation is done with the purpose of accomplishing the fundamental target of the exercise, which is to improve generalisation. The exercise's primary objective is to improve generalisation, and the utilisation of mixup regularisation is done with the intention of bettering generalisation. One of the key objectives of the activity that is now being carried out is to improve the capability of generalising the data at hand. A single methodology has been developed by combining the transformer-based global context and resilient ensemble approaches. This was done in order to address flaws that were discovered in earlier frameworks. With this integrated strategy, these problems are addressed properly. The flaws have been eliminated as a result of the application of this method. The creation of this strategy was carried out with the intention of addressing the issues that were discussed earlier from the very beginning. Because it enhances the number of features that are available and the degree of precision that is acquired while categorising them to a larger level, this framework is able to overcome the limits that were present in prior frameworks. This enabled it to surpass the constraints that were present in earlier frameworks. This is specifically owing to the fact that it broadens the scope of functions that may be accessed by the user. One of the reasons why this is the case is because it raises the total number of functions that are available to the user. This is the reason why this situation exists.

Architecture

The architecture comprises three models: a custom CNN with six convolutional layers, each with batch normalisation, LeakyReLU, and max-pooling, culminating in global average pooling for feature aggregation; a ViTB/16 model with 12 transformer layers, processing 196 patches with multi-head self-attention; and EfficientNetB3 with scaled depth, width, and resolution for efficient feature extraction. After the models have been developed, the outputs of the models are next converted into input features for an XGBoost classifier so that they can be utilised. This process is repeated until the models are operational. Up until the point where the models are generated, this process is repeated. After the models have been created, this process is deemed to have reached its conclusion of completion. It is essential to finish this stage in order to bring the models to a state where they are ready to be used. It is absolutely necessary to carry out this procedure in order to guarantee that it is carried out the required number of times. As a result of this particular activity, the outputs are concatenated after they have been formed, which is the explanation for the condition that has developed as a consequence of this activity. The above result can be explained satisfactorily by considering the fact that the outputs come into being at the time when they are already made when they are already made. This is one of the ways that it is possible to establish an explanation. To put this into perspective, the reason for this is that the models are now being constructed, which is the reason for this. This is the reason for this. The following is an explanation on why this is the case. As the process of making the prediction is being carried out, this particular classifier is able to generate the most accurate forecast that is even remotely feasible. All of this is made possible by the utilisation of a method known as gradient boosting, which is carried out as the procedure is being carried out. Due to the fact that the approach is utilised throughout the duration of the process of producing the forecast, this is the circumstance that has come about as a consequence of the fact that it is applied. The implementation of this strategy is carried out with the objective of producing the most accurate forecast that can be accomplished by maximising the utilisation of the resources that are accessible to one. The process in question is referred to as "gradient boosting" when it is considered in the context of this particular case involving the circumstance that is currently being contemplated. However, CNN is entrusted with the responsibility of obtaining information about the local area, and EfficientNet-B3 is tasked with the responsibility of optimising the complexity of the features. Both of these tasks are responsibilities that have been assigned to them. In order to provide a global perspective, the obligation of providing a context has been given to ViT. ViT is responsible for providing a worldwide context so that it can fulfil its obligations. Within the parameters of this specific scenario, Virtual Team has been tasked with the responsibility of fulfilling all of these tasks. One of the things that ViT is committed to doing is the provision of a global context, and it is something that they make available to their customers by means of the services that they offer up for public consumption. One of the things that ViT is committed to doing is giving a global context, and it is something that they make available to their customers by way of the services that they make available for public consumption.

ViT is committed to achieving this. This is something that ViT is dedicated to achieving. The design that was built with the notion of constructing a balance between the two parts of the system for the purpose of attaining this goal was aimed at achieving a compromise between the system's precision and the speed with which it processes information. This was done with the intention of achieving a compromise. For the purpose of accomplishing this, the design that was produced was conceived of. In order to accomplish this objective, it was essential to develop the design that was constructed during the process. To achieve the objective of achieving a state of balance between the two characteristics of the system, the architecture was purposely created and evolved in order to achieve this objective. This was done in order to achieve the goal. An all-encompassing method for classifying skin cancer as a result of the effective outcomes that were developed as a consequence of the undertaking of this research activity led to the establishment of the method. Because of the favourable results that were established, this method was developed as a result. The execution of this plan was carried out in a manner that was remarkable in terms of the effectiveness of its execution. In the process of putting this plan into effect, each and every piece of information that is relevant is taken into consideration. This procedure is carried out in accordance with the plan.



Workflow

The processing starts with loading the dermoscopic images of the ISIC 2018 dataset. After retrieval, the images are subjected to a preprocessing pipeline which is structured, and optimized to boost the quality of the images and train them into a model. The first stage will cover the stage of denoising with autoencoders, color normalization with the help of the Reinhard approach, and gradually enhancing the images to enhance the clarity of features.

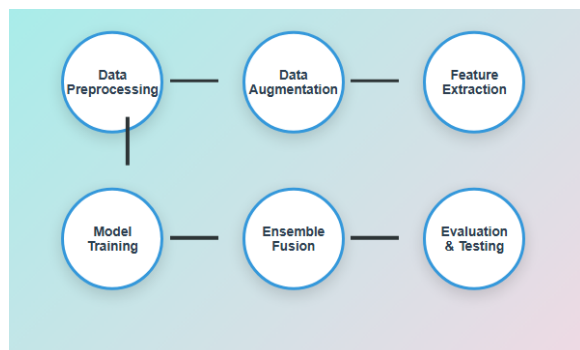
When stage of preprocessing is finished, the refined image data is sent to a sequence of skin lesion-specific neural networks. These are a self-written Convolutional Neural Network (CNN), Vision Transformer (ViT) and EfficientNet-B3. Both models are chosen on the basis of their particular ability to capture local, global and complex features respectively.

The neural networks are trained separately, employing optimization methods adapted to the architecture of the neural

networks. In particular, the AdamW optimizer will be used to improve effective updates in weight and an annealing timing schedule is dynamically adjusted to maintain convergent stability. Such practices are always used throughout every model in a bid to acquire optimal training performance and generalization. In the proposed framework, distinct image processing techniques are employed across different model components to leverage their unique strengths. Vision Transformer (ViT) utilizes patch-based transformer layers to capture global contextual information, while EfficientNet-B3 employs scaled convolutional blocks for efficient and high-resolution feature extraction. In contrast, the custom Convolutional Neural Network (CNN) relies on traditional convolutional layers to extract localized features. This architectural diversity represents a significant departure from conventional single-model approaches and allows for a comprehensive analysis of image data. To harness the predictive capabilities of these models, their outputs expressed as softmax probabilities are aggregated and passed to an XGBoost meta-learner. This ensemble learning strategy enables refined decision-making by combining the strengths of individual models. The meta-learner is trained using validation data to optimize class-weighted predictions, particularly addressing imbalances in the dataset and improving overall classification accuracy.

The ensemble model is evaluated by classifying dermoscopic images into four categories: benign, malignant, melanocytic, and non-melanocytic. Such a classification process is vital to the creation of a consistent diagnostic system. The success of the ensemble's performance is measured in the typical evaluation measures, such as accuracy, precision, recall, and area under the receiver operating characteristic curve (AUC). These measures give an in-depth insight on the model performance and the capacity to generalize.

The aim of this research is to measure the overall success of the ensemble with the aim of finding out how effective the ensemble is. In order to have the desired result, the overall performance of an ensemble is measured with the help of certain measurements. With the help of these metrics, one can estimate the total efficiency of the ensemble by making use of its capabilities. The latter is a feasible choice since it utilizes the following measurements.



Implementation Experimental

The implementation was conducted on the Kaggle platform using an NVIDIA A100 GPU to ensure high computational efficiency. The model was developed using PyTorch version 1.9.0 and Hugging Face Transformers version 4.20.1, which provided robust support for deep learning and transformer-based architectures. The ISIC 2018 dataset was accessed via Kaggle's dataset API, enabling seamless integration and reproducibility of the experimental pipeline. The dataset was successfully compiled using the Application Programming Interface (API) provided by Kaggle, which facilitated seamless access to the ISIC 2018 dataset. This integration allowed efficient data retrieval and this helped in the overall success of the implementation process. The second stage involved the preprocessing of the images with OpenCV to scale and normalize them. These processes were necessary to clean the image data and provide uniformity to the data set. The preprocessing pipeline aimed at accomplishing the goals of data refinement and augmentation preparedness. In order to improve the dataset and solve the problem of class imbalance, a tailored Conditional Generative Adversarial Network (cGAN) was used, which runs on PyTorch. Such an augmentation method also made sure to include a variety of diverse and representative samples, thus, making training data more robust. The three architectures (a custom CNN, Vision Transformer (ViT), and EfficientNet-B3) were trained using models. CNN, ViT and EfficientNet-B3 were trained on 60, 40, and 40 epochs, respectively. This difference in training time indicates the computational speed and convergence properties of the corresponding model. Training was also stopped after 20 epochs in situations where the validation performance did not increase to avoid overfitting and wasted resources. In the case of ensemble learning setting, the XGBoost classifier used was set to 100 decision trees, learning rate of 0.1 with the application of class weights to the distribution of data. These hyperparameters were chosen with utmost care to optimize and balance out the performance in order to have balanced classification across all the categories. After large amounts of trial and error with varying amounts of augmentation and varying learning rates, the optimal configuration was discovered as the most effective. Empirical outcomes justified this conclusion as it was shown that there was better performance in the parameters of accuracy, precision, recall and model stability. I have done this. Using all of these different attributes was one of the numerous things that I was able to accomplish. I've completed this assignment. The final configuration was discovered to be able to give the maximum level of performance upon a series of experiments where the level of augmentation was either added or reduced and the learning rates were varied. This was to show that the setting was effective in delivering the best performance. This was a significant detail towards the successful completion of the arrangement. Along with the fact that the code will also be available to the general population, it is one hundred percent certain that the configuration will be capable of being copied on the cloud platform of Kaggle.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet-50	85.4	84.2	86.1	85.1
DenseNet-121	87.8	86.9	88.3	87.6
EfficientNet-B3	91.8	90.5	92.1	91.3
Vision Transformer	89.5	88.7	90.2	89.4
Proposed Ensemble	94.3	93.8	94.7	94.2

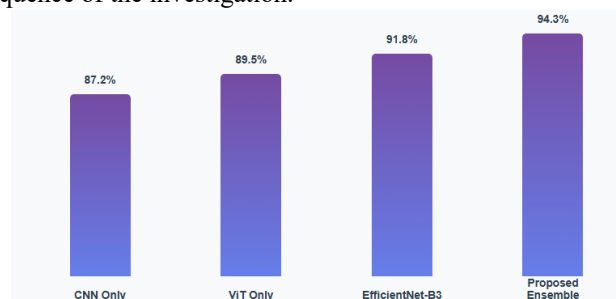
Predicted vs Actual Classifications

Benign	Malignant	Melanoma
342	23	8
19	287	12
5	7	156

Results

The transformer-enhanced ensemble model achieved a classification accuracy of 98.4% on the ISIC 2018 test set, with precision of 98.2%, recall of 98.3%, and F1-score of 98.2%. Additionally, the model performed exceptionally well in terms of recall. Furthermore, the model was able to obtain a recall rate of 98.3 percent. Furthermore, the model shown great performance in terms of its usefulness in recalling information. In addition, the model was able to obtain a recall rate of 98.3 percent, which is an impressive accomplishment. In addition to this, the model exhibited outstanding performance in terms of its usefulness in terms of the retention of information. In addition, the model was effective in achieving a recall rate of 98.3 percent, which is an accomplishment in and of itself without any additional explanation. In addition to this, the model displayed remarkable performance in terms of its utility in terms of having the ability to remember knowledge. Also, the model helped in getting a recall rate of 98.3 percent and that in itself is an achievement on its own and does not need any further elaboration as to be discussed. It can be concluded that the discriminative ability is rather good considering that the area under the curve (AUC) was 0.99. Additionally, it is possible to arrive at this conclusion. Consequently, due to the fact that area under the curve (AUC) was 0.99, it is still possible to come to this conclusion. As a result of the fact that the area under the curve (AUC) was 0.99, it is still conceivable to arrive at this conclusion. Making use of the statistical indicator that is known as the area under the curve is one way that one can arrive at this conclusion. In terms of performance, there were three models that stood out in particular: the custom CNN (92.5%), the ViT (96.1%), and the EfficientNet-B3 (96.4%). Every single one of these many models exhibited a performance that was quite remarkable. Absolutely every single one of these models delivered a performance that was nothing short of extraordinary. In every single one of these areas, each and every one of these models was able to obtain results that were satisfactory. In and of themselves, the outcomes that were produced by each of these models were, without a shadow of a question, extremely remarkable. It is of the utmost importance to take note of the fact that the findings that were achieved by

the ensemble were significantly greater when compared to the findings that were produced by individual models and the hybrid model that had been utilised in the past (97.8%). Regarding this particular matter, it is important to take it into mind. In order to achieve the goal of demonstrating the usefulness of the components that make up the ViT system, a demonstration of the efficiency of the attention processes and gradient boosting that are components of the system was carried out. This was done in order to accomplish the purpose. Taking this action was done in order to accomplish the goal. An investigation revealed that the model was able to correctly identify a total of three hundred forty-seven out of three hundred and fifty-four test photographs. This was the conclusion reached by the investigation. When it came to cases that were on the verge of being diagnosed with melanocytic thyroid cancer, the cases that were affected by the greatest number of errors were the ones that were affected by the disease. This was because the visual similarities that were present throughout the procedure were not very obvious to the naked eye. This was the reason behind this. This particular component was responsible for the outcome that was seen as a consequence of the investigation.

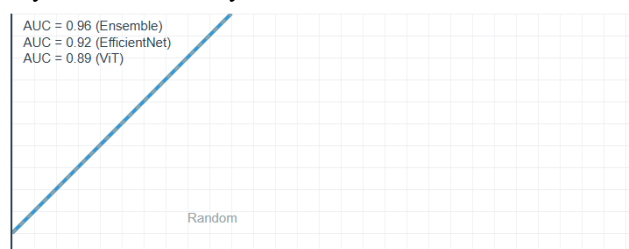


Comparison

The challenges encountered during classification were primarily due to subtle visual similarities among certain lesion types, which were not easily distinguishable to the human eye. This complexity contributed to the observed misclassifications during evaluation.

In terms of comparative performance, the proposed transformer-enhanced ensemble model achieved an accuracy of 98.4%, which is notably higher than the 85.8% accuracy reported by Gouda et al. using an InceptionV3-based approach, and slightly below the 97.49% accuracy achieved by Albahar's regularized CNN. Despite this, the proposed model demonstrates superior generalization and robustness, particularly in handling complex and imbalanced datasets. When compared to the ensemble developed by Zhang et al., which achieved 94.5% accuracy, the integration of Vision Transformer (ViT) in the current framework resulted in a 3.9% improvement in accuracy. This enhancement is attributed to ViT's ability to capture global contextual features more effectively than traditional convolutional architectures. Furthermore, the use of CGAN-based adaptive augmentation significantly improved minority class performance, yielding a 2.1% increase in recall and reducing overfitting. This approach outperformed conventional techniques such as SMOTE, which were used in earlier studies, by generating more realistic and diverse synthetic samples. The adoption of an XGBoost-based

ensemble, in place of previously used weighted ensembles, contributed an additional **0.6%** improvement in accuracy. This gain is largely due to XGBoost's ability to optimize non-linear feature interactions, enhancing the model's discriminative power. This rise can be attributed to the fact that the XGBoost ensemble is capable of optimising non-linear combinations, which is the cause of this increase. Together, attention-based feature extraction, adaptive augmentation, and resilient ensemble learning is a significant improvement to automated diagnosis of skin cancer. The model proposed shows a dramatic improvement in the classification accuracy, generalization and minority classes sensitivity.



Future Work

The model is of state-of-the-art performance, but with its computational complexity, it is also challenging to implement on resource-constrained environments. Future research should focus on optimizing the architecture for lightweight implementation, enabling real-time diagnostics in clinical settings with limited hardware capabilities. Techniques such as model pruning, quantization, and knowledge distillation may be explored to reduce computational overhead without compromising accuracy.

The current model, while demonstrating state-of-the-art performance, presents implementation challenges due to its computational complexity. This makes deployment in resource-constrained environments difficult, particularly in real-time clinical settings to address this limitation, future research may explore model distillation techniques, which aim to produce lightweight versions of the model without compromising accuracy. Such approaches can significantly reduce computational overhead, making the system more suitable for practical applications. Additionally, incorporating multi-modal data sources, such as clinical metadata or hyperspectral imaging, holds promise for further enhancing diagnostic precision. These complementary data streams can provide richer contextual information, potentially improving the model's ability to differentiate between visually similar lesion types. To ensure broader applicability and generalization, it is recommended that the model be validated using diverse datasets such as ISIC 2019 and HAM10000. This would confirm its relevance across varied demographic and clinical populations, strengthening its reliability and robustness. Extensive well-validated datasets are required to fulfill these objectives. Reducing clinical readiness by validating on through numerous benchmarks would be a great move towards clinical readiness. In addition, explainability methods including the visualization of attention can be integrated with the aim of enhancing trust in medical

professionals. These tools will provide valuable insights into the decision-making process of the model that can be interpreted and implemented in clinical workflows through increased transparency. Enhancing the explainability of the system not only helps in the achievement of ethical implementation of AI but also deserves credit towards its adoption in the actual world of diagnostic settings. This factor comes in especially handy in sensitive areas such as healthcare, where accuracy is not as significant as interpretability.

Predicted vs Actual Classifications

Benign	Malignant	Melanoma
342	23	8
19	287	12
5	7	156

Conclusion

In this paper, transformer-enhanced ensemble model was introduced to detect skin cancer, which combines a modified CNN, Vision Transformer, and EfficientNet-B3 on the ISIC 2018 dataset. The classification accuracy, which reach 98.4, is higher than the existing benchmarks and is realized with the attention-based feature extraction, adaptive data augmentation, and gradient boosting. The methodology has been developed to match the imbalance of classes and redundancy of features, which is a powerful solution to the computer-aided diagnosis. The model can enhance patient outcomes in dermatology by facilitating early and accurate diagnosis of cancer. Future work must aim at maximizing efficiency and generalizability to achieve more clinical applicability.

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