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Advanced Detection and Classification of Corneal Ulcer by Densenet121 Feature Extraction and SVM Classifier

Abstract: Keratitis of the eye is caused by a disorder called corneal ulceration. The cornea is the primary portion of the eye that protects the iris and pupil. Corneal ulcers are a disorder that can be caused by an eye infection or injury. This disease is difficult to detect early due to its complex and silent progression. Deep Convolutional neural networks were used in this study along with many other techniques and approaches for early detection of corneal ulcers. DCNN-based technology works similarly to the human brain. To review the various ML and DL algorithms available for corneal ulcer classification models. Developing a model to predict corneal ulcer types, types, and grades using deep learning (DL) techniques. Test the performance of evaluated by various evaluation metrics and compare with existing methods.

Keywords: Densenet121, Svmclassifier.

1. INTRODUCTION

Corneal ulcer (CU) is the worst base for the cause of ocular disease worldwide and most common symptom of corneal disease. Irreversible visual impairment or blindness are severe cause of CU and it require an innovative strategy to differentiate between different types of ulcer stages in order to reduce the overall burden of visual impairment. Ocular trauma, especially corneal ulcers (CU), is the most serious cause of corneal blindness, potentially leading to 1.5 to 2 million new cases of monocular blindness each year (Whitcher et al., 2001)[43].
The challenge is to predict corneal ulcer outcome while considering characteristics such as location, size, and visual acuity. At the same time the ulcer's size cannot be measured precisely. To measuring ulcer severity, corneal ulcers must be detected effectively and their areas were segmented. As a result, accurate and automated detection and segmentation of corneal ulcers will aid in disease diagnosis. Digital image processing has recently enabled automated discovery and cost-effective diagnosis of corneal ulcers.it is successfuly by the application of digital image processing, machine learning (ML) and deep learning (DL) techniques. . (Chun et al., 2014; Tzelepi & Tefas, 2018). Accordingly, this study focuses on developing a corneal ulcer prediction model using deep learning (DL) techniques [38].

LITERATURE SURVEY

Akram & Debnath (2019) developed CNN model to analyse facial images for corneal ulcer disease using CNN with the help of facial images [1]. The proposed system achieves the accuracy, sensitivity and specificity of 99.43%, 98.785 and 98.6% by augmentation**.**
Tan et al. (2020) used feature graph in altered VGG network for corneal ulcer classification to achieve feature fusion [36]. Before training his modified VGG model, data preprocessing techniques such as AHE, normalization, masking, and data augmentation were performed on his CU images. The results identified that the altered VGG network performed better than the traditional CNN network with fewer parameters. The modified VGG network achieved accuracy, sensitivity, and precision of 88.89%, 71.93%, and 92.27%. It is concluded that data preprocessing and weighting loss functions can significantly improve network classification effectiveness. Jiang et al. (2021) classified keratitis by pre-trained models such as DenseNet121, ResNet50, and Inception, other corneal abnormalities, and normal cornea [29] and 6567 slit lamp images from various sources were used to train the model and found that Dense Net attained the accuracy of 96%.
Teeyapan (2021) presented a deep transfer learning architecture to identify the changes between early and advanced stages of corneal ulcer [37]. The basic model taken from deep convolutional neural networks were trained and tested with fluorescent-stained slit-lamp images from the publicly available SUSTech-SYSU dataset [13]. ResNet50 was found to be the best model, achieving an accuracy of 95.1%, sensitivity of 94.37%, F1 score of 95.04%, and Cohen's Kappa of 0.9021.

1. Data Collection and Preprocessing

A crucial primary step in developing a deep learning (DL) model for accurate corneal ulcer prediction is assembling a dataset consisting of corneal images obtained through advanced imaging methods such as slit lamp bio microscopy or optical coherence tomography (OCT) of the anterior segment [17].

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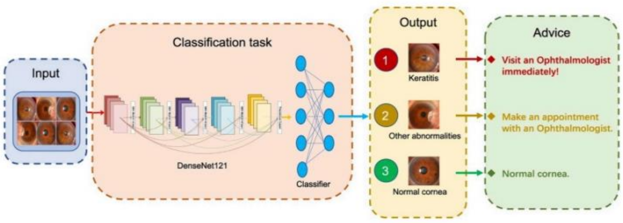
This dataset is enriched with relevant clinical data, including patient demographics, medical history, and symptoms specifically related to corneal ulcers. An important aspect of this process is the duration and meticulous annotation of the dataset, a task performed by professional ophthalmologists. Their expertise ensures the accuracy and consistency of the dataset, providing the basis for training a robust DL model capable of accurately predicting corneal ulcers.

2. Existing Model

In the process of developing deep learning (DL) models to accurately predict corneal ulcers, an important existing framework as presented in Figure 1 has been developed for early detection of keratitis, a condition that can lead to corneal blindness when using deep learning models. (DL). Identify the most effective deep learning model for classifying corneal conditions into three categories such as keratitis, cornea with other abnormalities, and normal cornea using three convolutional neural network architectures This study utilized (CNN) such as DenseNet121, Inception-v3 and ResNet50. It uses a large dataset of slit lamp images collected from multiple institutions, including clinical images and smartphone images such as slit lamp images, to train and test the model. The dataset consisting of more than 7,000 slit lamp images from a variety of sources. This large and diverse dataset allows for better training and testing of deep learning models, increasing generalizability to different situations. To evaluate the model's reliability and generalizability, the model was tested with three additional external datasets from different organizations as well as smartphone-based datasets. This external validation adds confidence to the model's performance. This model was developed with a focus on keratitis detection and addresses a real-world medical problem with important implications for visual health. Early detection of keratitis can prevent corneal blindness, making this study highly relevant to clinical practice. The first step is to assemble a dataset consisting of corneal images obtained through advanced imaging methods such as anterior segment optical coherence tomography (OCT) or slit lamp bio microscopy. [17]. this dataset is enriched with relevant clinical data, including patient demographics, medical history, and symptoms specifically related to corneal ulcers. An important aspect of this process is the duration and meticulous annotation of the dataset, a task performed by professional ophthalmologists. Their expertise ensures the accuracy and consistency of the dataset, providing the basis for training a robust DL model capable of accurately predicting corneal ulcers.

Fig 1. Existing model for corneal ulcer classification (Li et al. 2021)



5. Proposed Model

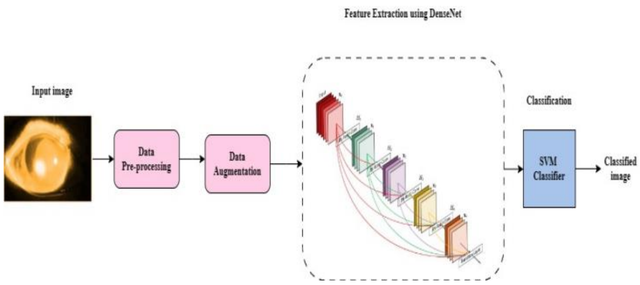


Fig 2. Corneal VisionNet architecture

The proposed model aims to address the challenge of accurately predicting the presence of corneal ulcers. Corneal ulcers are open sores on the cornea, if its not treated properly then it will result infections or injuries. Early and accurate prediction of corneal ulcers is important for timely intervention and improved patient outcomes [3]. Our proposed model shows the important progression in the field of corneal ulcer prediction, driven by several key innovations that collectively enhance its effectiveness and practical utility. Firstly, our model incorporates deep learning techniques, which have proven to be highly effective in processing complex data patterns. Deep learning enables the system to automatically extract intricate features and relationships from the input data, in this case, likely risk factors for corneal ulcers. This deep learning aspect allows for more accurate and precise predictions compared to traditional methods. Secondly, transfer learning was used that leverages pre-trained models to kick start our system's learning process [19]. By building on the knowledge acquired from other relevant domains or datasets, our model can expedite its understanding of corneal ulcer prediction. This not only accelerates development but also improves the execution of the model, devising it much robust and adaptive to different scenarios.

5.1. Model Architecture

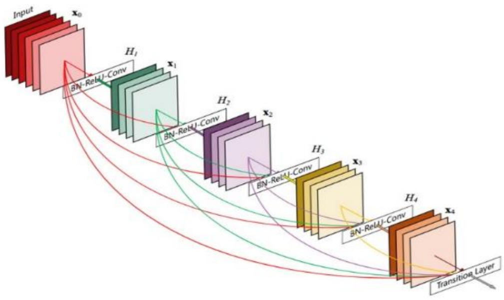


Fig 3. Architecture of Dense Net121

The projected framework uses DenseNet121, with convolutional neural network (CNN) recognized for its proficiency in image classification tasks. To adapt it for the specific task of corneal ulcer prediction, a series of architectural modifications are introduced. Initially, Global Average Pooling is applied to the output of the base CNN model, a technique used to reduce the spatial dimensions of the feature maps, thereby capturing essential information while minimizing computational complexity. DenseNet121 operates on input images of a standardized size, specifically RGB images with dimensions of 224×224 pixels. The architecture of DenseNet121 is characterized by its depth, consisting of a total of 121 layers, housing more than 8 million parameters as shown in Fig 3. DenseNet-121 architecture comprises the following components such as 5 convolutional and pooling layers, 3 transition layers (specifically positioned at layers 6, 12, and 24), 1 Classification layer (located at layer 16) and 2 Dense Blocks which consists of 1×1 and 3×3 convolutions. The network is organized into distinct building blocks known as Dense Blocks. Within each Dense Block, the feature maps maintain consistent dimensions, although the number of filters or channels varies across different layers. These variations in filter count enable the network to capture different levels of features and abstractions. To facilitate the transition between these Dense Blocks, transition layers are introduced. These transition layers perform down-sampling, reducing the spatial dimensions of the feature maps. Additionally, they incorporate batch normalization techniques to normalize the activations, a process that aids in training stability and faster convergence.

5.2 Feature Extraction Using Densenet121

DCNN has been successful in solving image classification problems. Every layers in convolutional neural network (CNN try to capture important features from input data. CNN architectures were built by three types of layers: convolution layers, pooling layers, and fully connected (fc) layers [17]. The model architecture is based on DenseNet121, a pre-trained convolutional neural network (CNN) that excels at image classification tasks.

The ReLU activation function is used, because it is computationally efficient because it involves only a simple thresholding operation. This helps speed up training compared to more complex activation functions. The global Average Pooling is applied to the output of the base CNN model to reduce spatial dimensions. Three separate output branches are added to the model for category, type, and grade predictions, each using softmax activation to produce probability.

5.3 Transfer Learning

A key challenge is the scarcity of labelled data specifically tailored for precise corneal ulcer prediction, to address this limitation, a powerful technique called transfer learning is employed. Initially, a Convolutional Neural Network (CNN) is pretrained on a considerably larger and more diverse dataset consisting of general eye images, which may include retinal images or anterior segment images. This pertained model has already acquired the capability to recognize fundamental eye structures and features, which is valuable knowledge for corneal ulcer prediction. Subsequently, the pretrained CNN model undergoes a process known as fine-tuning, using the smaller dataset containing corneal ulcer images. During fine-tuning, the model adapts and specializes its learned representations to the unique characteristics and patterns associated with corneal ulcers. This transfer of knowledge from general eye images to corneal ulcers significantly enhances the ability of model to produce faithful predictions in the context of corneal ulcer detection, despite the limited availability of corneal ulcer-specific labelled data. Essentially, transfer learning leverages the existing wealth of knowledge to bridge the data gap and improve the performance of the model in a specific medical domain like corneal ulcer diagnosis.

5.4Integration of Clinical Data

In this model, an innovative approach involves the integration of not only corneal images but also pertinent clinical data. This clinical data encompasses a wide range of information, such as patient demographics, medical history and the symptoms associated with corneal ulcers. To make this clinical data compatible with the DL model, it undergoes a preprocessing step where it is processed and encoded into a format suitable for seamless integration with the convolutional neural network (CNN). By incorporating clinical data alongside the corneal images, the proposed model achieves a holistic understanding of the corneal ulcer prediction task. It leverages the visual information extracted from the corneal images, which provides valuable insights into the actual state of the cornea. Simultaneously, it takes into account the contextual information provided by the clinical data, including the patient's background and medical history, which may contain crucial factors influencing the likelihood of corneal ulcers. This combined approach allows the DL model to make up a broad and multidimensional representation of the component contributing to the transformation of corneal ulcers [19]. By fusing visual and clinical information, the model can better discern subtle patterns and relationships that might not be evident when considering each data source in isolation. Ultimately, this integration enhances the model's accuracy and efficacy in predicting corneal ulcers, offering a more informed and nuanced assessment of this medical condition.

5.5Training and Validation

The collected dataset, contains corneal images and associated clinical data, works as the foundation for training the model. During training, optimization techniques like Stochastic Gradient Descent (SGD) and back propagation are employed to iteratively alter the hypothesis parameters. These techniques help the model learn and identify complex patterns and features within the data by fine-tuning its internal representations. The dataset is commonly separated into two subsets: a training set and a validation set. The training set is used to update the model's parameters, and the validation set is used to track the model's performance during training. This split enables the early detection of overfitting, and provide depth understanding of poor and best performance of unseen data [25].

5.6Explainability and Interpretability

The incorporation of techniques for model explainability is a critical step aimed at improving transparency and interpretability. This involves generating visualizations that highlight the regions of interest and key features identified by the model within the corneal images. These visualizations are useful for understanding how the model makes decisions. By revealing the particular areas in the corneal images helpful for the medical practitioners to gain a advisable understanding of the model's output. This transparency not only helps build trust in the DL model's capabilities but also allows medical professionals to validate the model's findings based on their domain expertise. Additionally, it provides a means to pinpoint potential areas of concern or interest in the images, aiding in the clinical assessment and diagnosis of corneal ulcers. These explainability techniques enables clinicians to collaborate effectively with the DL model, leveraging its capabilities while maintaining a clear understanding of how and why it arrives at particular predictions. This fosters a more robust and trustworthy partnership between artificial intelligence and medical experts, facilitating the accurate diagnosis and treatment of corneal ulcers while ensuring that clinical decisions are well-informed and grounded in both data-driven insights and clinical expertise.

5.7Model Evaluation and Validation

A critical phase in the development of a Deep Learning (DL) model for accurate corneal ulcer prediction is the rigorous evaluation of the model's effectiveness and reliability. This evaluation is carried out using an independent test dataset, which comprises corneal images and their associated clinical data. This dataset differs from the one used for training and validation, ensuring that the model is tested on previously unseen cases. During the evaluation process, the performance of the model was measured and compared against existing models or methods that are commonly used for corneal ulcer prediction. The performance of the model was evaluated by accuracy, Recall, Precision and F1 score.

Accuracy

Accuracy is a measure of the correct prediction in overall classification and its denoted as (2);

Accuracy= (TP+TN)/ (TN+FP+FN+TP) (2)

Precision

Precision is the ratio of accurately predicted observations to the total predicted positive observations. The expression for precision was given in equ (3);

Precision=TP/ (TP+FP) (3)

Recall

Recall is a performance metric in machine learning and statistics that measures a model's ability to correctly identify all related instances in a dataset. It measures the proportion of true positive predictions (correctly identified positive instances) among all actual positive instances in the dataset. The expression for Recall was given in equation (4);

Recall=TP/ (TP+FN) (4)

F1 score

The F1 score is the weighted average of precision and recall. It is applied as a statistical fact to assess the classifier's performance, which considers both false positives and false negatives . It denoted as follows. (5);

F1-Score = (2*Recall*Precision)/(Recall+Precision) (5)

Where TP is True Positive, TN is True Negative, FP False Positive and FN is False Negative.

6. Training the model

The actual training of the DL model takes place as follows:

6.1Data Preparation:

In the initial phase of building the "Predictive Analysis of Corneal Ulcer Disease" model, the data is meticulously prepared. This begins with loading the essential information, such as image filenames and their corresponding labels (categories, types, and grades), from an Excel file. These labels provide the ground truth for the model to learn from. To locate and access the actual images, paths are constructed by combining the image folder path with the image filenames. Subsequently, the data is partitioned into distinct sets for training and validation, ensuring that the model can be effectively trained and evaluated. The “Custom Data Generator” function generates batches of images and their corresponding labels. It takes input parameters such as image paths, categories, types, grades, batch size, image height, and image width. The generator shuffles the indices of the samples to ensure randomization and yields batches of images and labels during training.

6.2Data Preprocessing and Augmentation

The data preprocessing was carried out by rescalling, flipping horizontally and vertically, as well as random rotations augmentation before being fed into the model and the image pixel values to make sure they are between 0 and 1. The training process is facilitated by this standardization. By subjecting the model to a range of visual transformations and orientations, augmentation helps to improve the model's capacity for generalization.

6.3Model Architecture

The heart of the predictive analysis model lies in its architecture. Here, the DenseNet121 pre-trained model takes center stage as the base model. DenseNet121 is a deep convolutional neural network (DCNN) with a significant number of layers. In the model architecture, spatial dimensions of the data was reduced by global average pooling. Subsequently, separate output layers are introduced for each prediction task: category, type, grade, and even SVM (Support Vector Machine) output. These layers plays prominent role in the model's predictions and outputs for several aspects of corneal ulcer classification.

Using supervised learning, SVM is a machine learning algorithm that categorizes data into groups and analyzes it for the classification problem. SVM seeks to provide a learning technique that is computationally efficient by dividing hyper planes in a high-dimensional feature space. Classifying the two sets of data is possible with many hyper-planes.

That hyper-plane with the biggest margin is the ideal one to choose. The margin is the maximum width that the boundary could reach before making contact with a data point. The term "support vectors" refers to the data points that the margin raises. The SVM's objective is to ascertain the ideal hyperplane that splits the target vector cluster on the other side of the plane. The Support Vector Machine (SVM) models are trained and evaluated separately for category, type, and grade predictions. Each SVM classifier (svm_category, svm_type, svm_grade) is trained on the normalized input features (X_train) and their respective labels (y_category_train, y_type_train, y_grade_train). The classification used test set (X_test), and accuracy scores were calculated by ‘accuracy score’ function.

6.4Model Compilation

Once the architecture is defined, the model is compiled. This involves configuring several crucial elements. Specifically, loss functions are assigned to each output, with categorical cross-entropy employed for category, type, and grade outputs. For the SVM output, hinge loss is selected. Additionally, optimization is handled using the Adam optimizer, a popular choice in deep learning. This step prepares the model for training by specifying how it should assess its own performance and how it should update its internal parameters.

6.5Custom Data Generator

To efficiently handle the large volume of image data, a custom data generator function is designed. This function plays a pivotal role in generating batches of images and their associated labels. It accepts various inputs, including image paths, categories, types, grades, batch size, image height, and image width. The generator's functionality encompasses shuffling the indices of the samples and yielding batches of images and labels, ensuring that the model is fed with data in an organized and manageable manner during training. The dataset is split into 80% for training and 20% for testing. This ensures a separate set of data for evaluating the performance of the model.

6.5Model Training:

With the data generator in place, the model can be trained effectively. The “model. Fit ()” function is invoked to initiate the training process. The generator designed for training data is provided as input, facilitating the flow of images and labels to the model during each training iteration. Various epoch and batch size were used to identify the architecture performance. Similarly, a validation generator is configured to assess the model's performance during training. The number of validation steps is computed in a similar fashion. The “Model Checkpoint” callback is utilized to save the weights for each epoch, to alter the preservation of the model’s progress

6.6Training Progress and Performance

Throughout the training process, various metrics were used to assess the progress and execution of the model. The history object serves as a repository for these metrics, capturing essential information such as loss and accuracy for each output. These metrics are critical in evaluating how well the model is learning and making predictions. They provide insights into how the model is adapting to the training data and whether it is converging to an effective solution. The metrics stored in the history object offer a broad view of the model’s operation and guide decisions related to model adjustments and fine-tuning, ultimately leading to the development of a robust and accurate predictive analysis model for corneal ulcer disease.

2. RESULTS AND DISCUSSION

The entire research was carried out using a system equipped with an Intel Core i7-7700HQ processor, an extra GPU (NVIDIA GeForce GTX 1060 with 6 GB of GDDR5 memory), a 512 GB SSD storage, and utilizing Keras with Tensor flow as the backend framework. The outcomes and outputs of all the models were executed through OpenCV and the Python programming language.

The SUStech-SYSU dataset comprises 712 corneal ulcer images categorized by the ulcer’s type, pattern, and severity level was used in this study.

The Fig 4 highlights the different categories of corneal ulcers and their characteristic patterns. The corneal ulcers in the upper row are pointed in appearance, the corneal ulcers in the middle row are a mix of pointy and flaky, and the corneal ulcers in the lower row are primarily flaky. Figure 5 depicts the various forms of corneal ulcers, whereas Figure 6 shows the various grades of corneal ulcers.

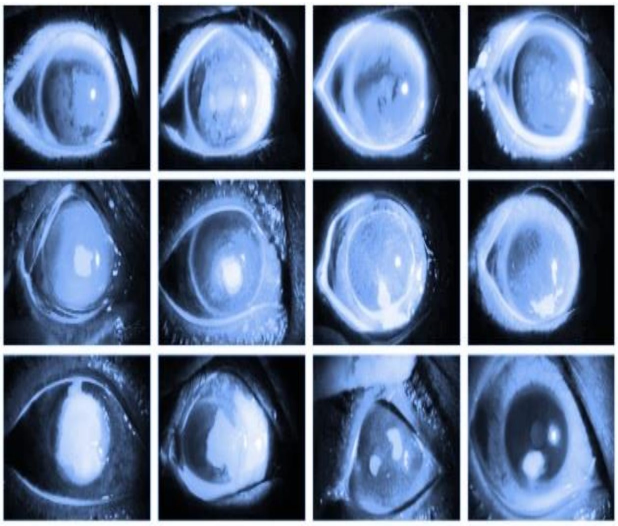


Fig 4. Different forms of corneal ulcers

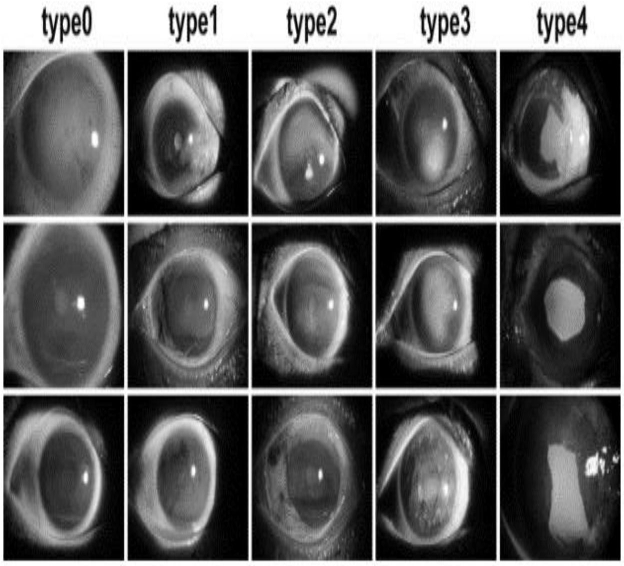


Fig 5. Types of corneal ulcers

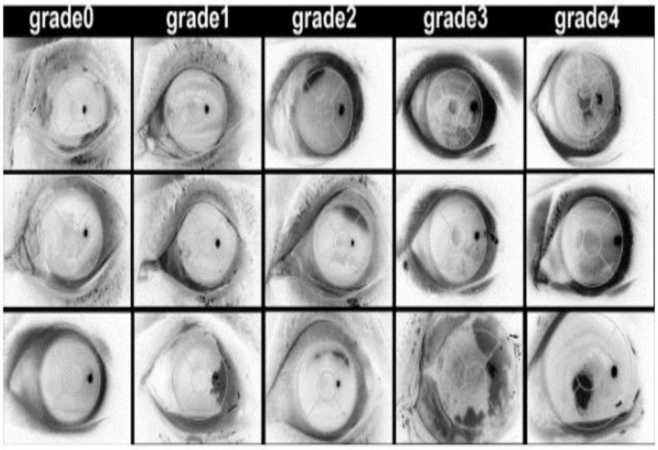


Fig 6. Grades of corneal ulcers

7.1 Accuracy of Proposed and Existing Models

This study achieved a high accuracy across all categories, types, and grades of corneal ulcers. The category accuracy of 0.9537, type accuracy of 0.9565, and grade accuracy of 0.9073 highlight the ability of the model to correctly classify corneal ulcers.

Table 1 and Figure 7 presented the category accuracy of existing models such as Resnet101, NASNet as well as Proposed CornealVisioNet in categorizing corneal ulcers. Resnet101 achieved a commendable accuracy of 85.8%, suggesting its ability to correctly classify a substantial portion of corneal ulcers. However, there is opportunity for improvement to enhance its accuracy and reduce misclassifications. NASNet, with an accuracy of 76.3%, exhibits good performance but indicates some challenges in accurate categorization. Further refinement of its architecture or training data may be necessary. The proposed CornealVisioNet offers an impressive accuracy rate of 95.37%. The category accuracy of Proposed CornealVisioNet model was 11.1% and 24.9% higher than the existing Resnet101 and NASNet model. This suggests that the Proposed CornealVisioNet is a robust tool for categorizing corneal ulcers, offering valuable support to healthcare professionals in accurate diagnosis and treatment decisions. The high accuracy of CornealVisioNet underscores its promise in clinical settings where precise categorization of corneal ulcers is crucial for patient care.

Table 1. Category accuracy of proposed and existing models

Model	Accuracy (%)
Resnet101 (Wang et al. 2020)	85.8
NASNet (Daoud et al. (2022)	76.3
Proposed CornealVisioNet	95.37

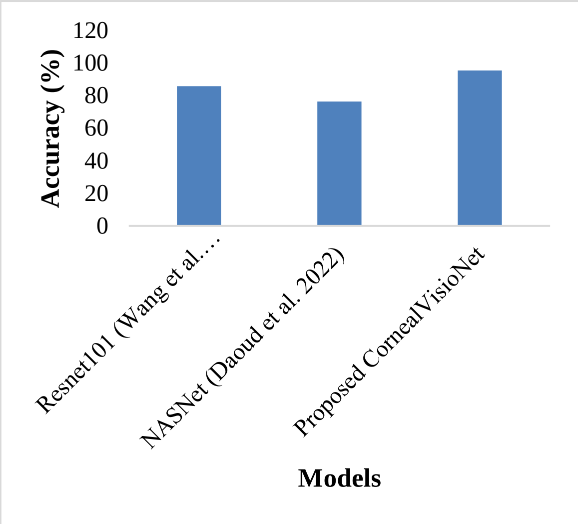


Fig 7. Category accuracy of proposed and existing models

Table 2 and Figure 8 presented the accuracy for the types of corneal ulcers of various models such as Modified VGG network, CNN, NASNet, AlexNet and proposed CornealVisioNet. The NASNet gives an accuracy of 96.8%, indicating its exceptional ability to correctly classify different types of corneal ulcers. This high accuracy holds great promise for accurate diagnosis and treatment decisions in clinical practice. The CNN also demonstrates strong performance with an accuracy of 92.73%, showcasing its reliability in identifying and categorizing corneal ulcers. The modified VGG network, with an accuracy of 88.89%, and AlexNet, with 80.42% accuracy, provide reasonably good results, although there may be room for improvement in specific scenarios or with more diverse datasets. The proposed CornealVisioNet exhibits a accuracy of 95.65% highlighting its potential as a worth tool for assisting healthcare professionals in accurate detection of types of corneal ulcers.

Table 2. Type accuracy of proposed and existing models

Reference	Accuracy (%)
Modified VGG network (Tang et al. 2020)	88.89
CNN (Gross et al. 2021)	92.73
NASNet (Daoud et al. 2022)	96.8
AlexNet (Cinar et al. 2022)	80.42
Proposed CornealVisioNet	95.65

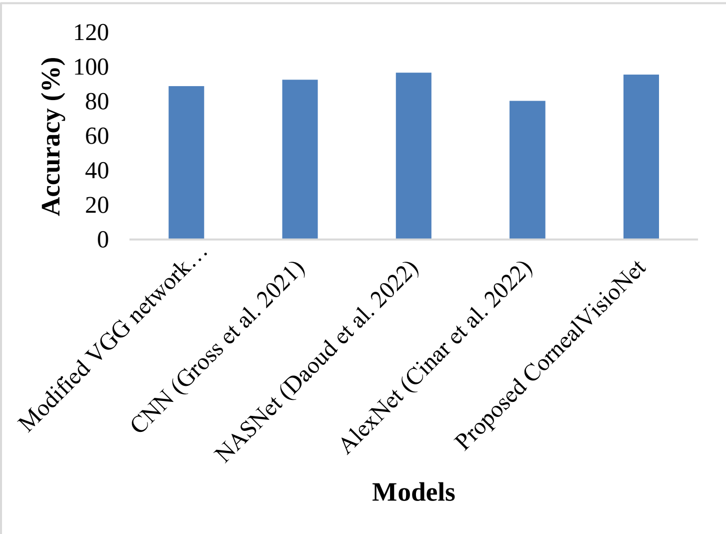


Fig 8. Type accuracy of proposed and existing models

Table 3 and Figure 9 presented the accuracy detecting the grade of corneal ulcers of existing model such as DCNN, NASNet, ResNet101 with PCA and Proposed CornealVisioNet. The NASNet possess an exceptional accuracy of 98.2%. DCNN also demonstrates a commendable performance with an accuracy of 95.1%, indicating its reliability in grade detection. ResNet101 with PCA follows closely with a 93% accuracy rate. The Proposed CornealVisioNet have an accuracy of 90.73%, presents a respectable level of performance, although there may be room for further refinement to enhance its precision in grading corneal ulcers. This signifies its outstanding accuracy in discerning and categorizing the severity or grade of corneal ulcers, which is of utmost importance in clinical practice for determining appropriate treatment strategies.

Table 3. Grade accuracy of proposed and existing models

Model	Accuracy (%)
DCNN (Teeyapan, 2021)	95.1
NASNet (Daoud et al. (2022)	98.2
ResNet101 with PCA (Alquran et al. 2022)	93
Proposed CornealVisioNet	90.73

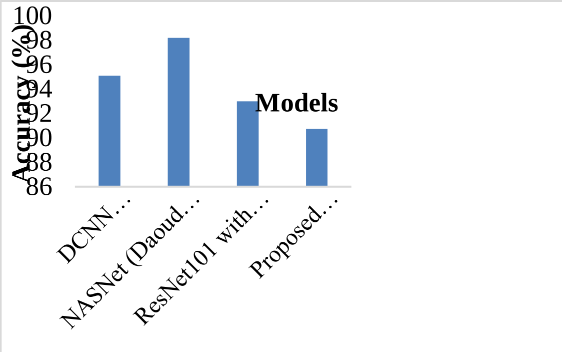


Fig 9. Grade accuracy of proposed and existing models

7.2 Precision of Proposed and Existing Models

It measures the dimension of supportive cases that are correctly predicted among all cases that are predicted to be positive. The accuracy scores for categories, types, and notes are impressive, with values of 0.9563, 0.9883, and 0.9897, respectively. These scores show that the model is highly accurate in identifying corneal ulcers of each type, and grade.

Table 4 and Figure 10 presented the precision rate of detection of categories of corneal ulcers of existing NASNet and Proposed CornealVisioNet. The proposed CornealVisioNet offers a precision of 95.37%, indicating its exceptional precision in correctly identifying and categorizing corneal ulcers. This high precision is a crucial aspect in medical image analysis, particularly in the context of corneal ulcers, where misclassifications can have significant implications for patient care. NASNet, while still demonstrating a precision of 80.5%, which is about 15.5% lesser than the proposed CornealVisioNet in terms of precision.

Table 4. Category Precision of proposed and existing models

Reference	Precision (%)
NASNet (Daoud et al. (2022)	80.5
Proposed CornealVisioNet	95.37

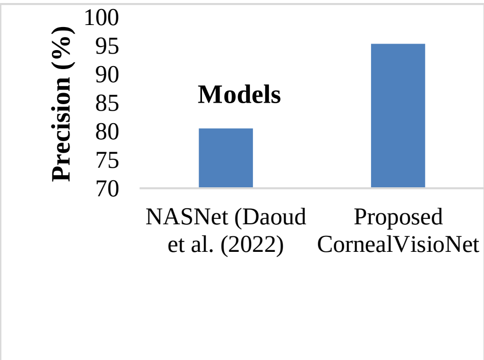


Fig 10. Category Precision of Proposed and Existing Models

Table 5 and Figure 11 presented the precision rate of detection of types of corneal ulcers of existing VGG network, NASNet, and Proposed CornealVisioNet. The NASNet exhibits commendable precision with a score of 95.7%, highlighting its ability to accurately and reliably detecting the types of corneal ulcers. The Modified VGG network, while still demonstrating a precision rate of 92.27% which is found to be slightly lesser than the NASNet. The proposed CornealVisioNet closely follows with a precision of 95.65%, indicating its strong performance in precisely identifying types of corneal ulcers. The precision plays a pivotal role in the medical field, where the accurate identification of specific ulcer types is paramount for providing tailored patient care. The high precision of Proposed CornealVisioNet suggests their potential as valuable tools for healthcare professionals in enhancing the precision of corneal ulcer diagnosis and treatment decisions.

Table 5. Type Precision of proposed and existing models

Reference	Precision (%)
Modified VGG network (Tang et al. 2020)	92.27
NASNet (Daoud et al. 2022)	95.7
Proposed CornealVisioNet	95.65

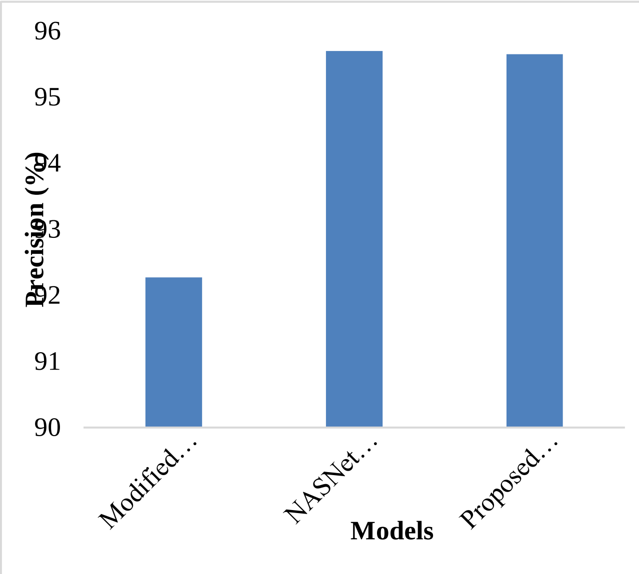


Fig 11. Type Precision of Proposed and Existing Models

Table 6 and Figure 12 presented the precision rate of detection of grade or severity of corneal ulcers of existing NASNet and proposed CornealVisioNet. The NASNet demonstrates strong precision with a score of 95.1%, indicating its ability to accurately and reliably assess the grade of corneal ulcers. This precision is pivotal in clinical practice, where the severity of ulcers guides treatment decisions. Proposed CornealVisioNet also presents a respectable precision of 90.73%, suggesting its competence in grading corneal ulcers.

Table 6. Grade Precision of proposed and existing models

Reference	Precision (%)
NASNet (Daoud et al. 2022)	95.1
Proposed CornealVisioNet	90.73

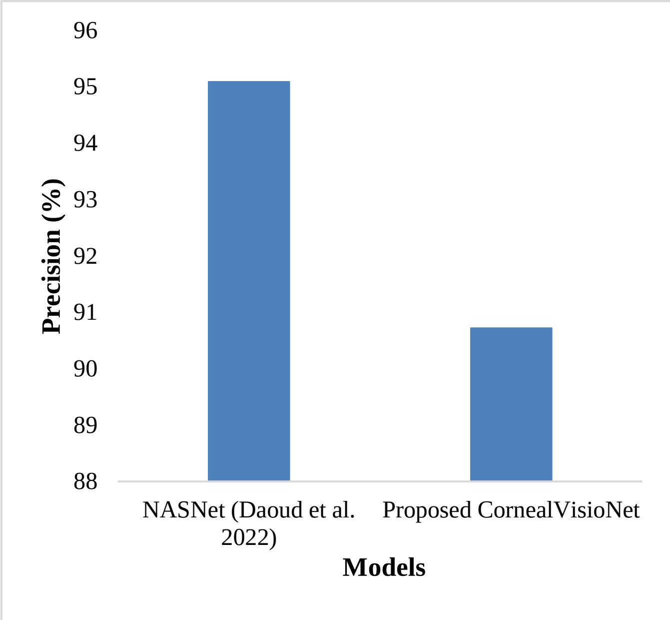


Fig 12. Grade Precision of proposed and existing models

7.3 Recall of Proposed and Existing Models

Recall, also known as sensitivity, is the proportion of accurately anticipated positive instances to all actual positive instances. The recall scores for category, type, and grade are excellent, with values of 0.9887, 0.9970, and 0.9985, respectively. These scores demonstrate the model's ability to effectively capture and identify corneal ulcers in each category, type, and grade.

Table 7 and Figure 13 presented the recall of detection of categories of corneal ulcers of existing NASNet and proposed CornealVisioNet. The proposed CornealVisioNet gives a recall of 98.87%, signifying its exceptional capability to effectively retrieve and identify instances of corneal ulcers within the specified categories. This high recall rate is particularly valuable in the medical field, where comprehensive identification of specific ulcer types is crucial for accurate diagnosis and treatment. In contrast, NASNet demonstrates a lower recall of 57.1%, suggesting that it may have difficulty in capturing all instances of corneal ulcers within the defined categories. A lower recall rate could lead to missed diagnoses or treatment delays.

Table 7. Category Recall of proposed and existing models

Reference	Recall **(%)**
NASNet (Daoud et al. 2022)	57.1
Proposed CornealVisioNet	98.87

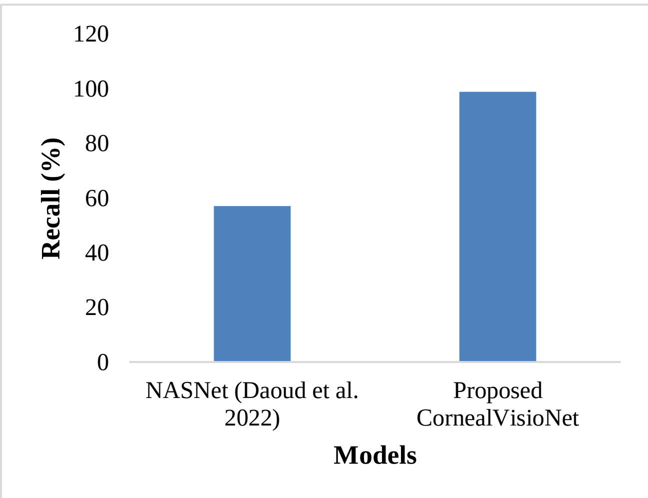


Fig 13. Category Recall of Proposed and Existing Models

Table 8 and Figure 14 presented the recall of detection of type of corneal ulcers of existing NASNet and proposed CornealVisioNet. The proposed CornealVisioNet exhibits an exceptional recall rate of 99.70%, which signifies its outstanding ability to comprehensively retrieve and correctly classify instances of various corneal ulcer types. This remarkably high recall rate is of paramount importance in medical image analysis, where the accurate identification of specific ulcer types is fundamental for precise diagnosis and tailored treatment plans. In contrast, NASNet also demonstrates a strong recall of 95.7%, which is commendable but slightly lower than that of Proposed CornealVisioNet. This suggests that NASNet may have a marginally lower capacity to capture and categorize all instances of corneal ulcers across different types.

Table 8. Type Recall of proposed and existing models

Reference	**Recall (%)**
NASNet (Daoud et al. 2022)	95.7
Proposed CornealVisioNet	99.70

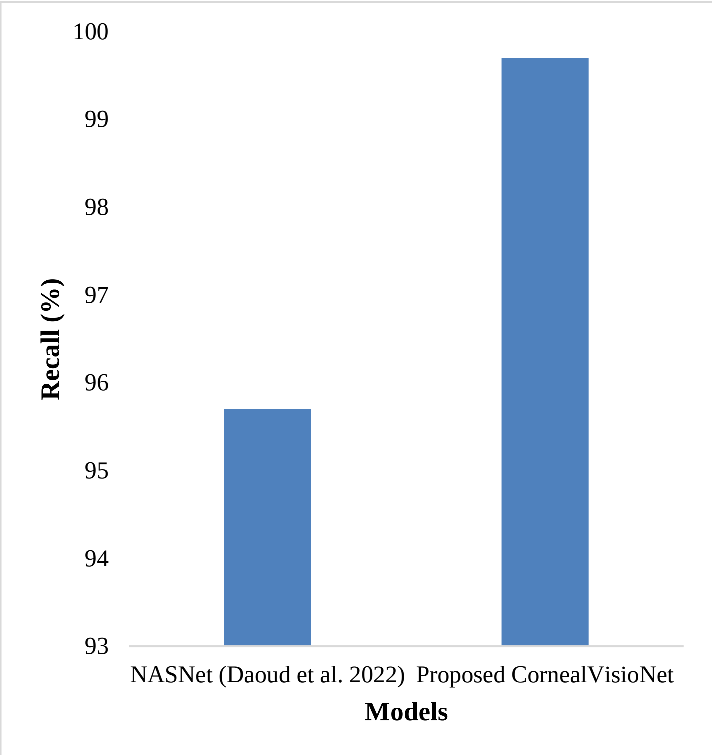


Fig 14. Type Recall of Proposed and Existing Models

Table 9 and Figure 15 presented the recall of detection of grade or severity of corneal ulcers of existing NASNet and proposed CornealVisioNet. The proposed CornealVisioNet stands out remarkably with an exceptionally high recall rate of 99.70%, indicating its exceptional ability to comprehensively retrieve and correctly categorize instances of varying ulcer grades. This high recall rate is of paramount importance in the medical field, where the precise assessment of ulcer severity guides treatment decisions and patient care. NASNet also demonstrates a strong recall of 95.7%, which is commendable but slightly lower than that of Proposed CornealVisioNet. This suggests that while NASNet is effective in capturing and categorizing a significant portion of ulcer grades, it may miss some instances, potentially leading to variations in grading accuracy.

Table 9. Grade Recall of proposed and existing models

Reference	Recall **(%)**
NASNet (Daoud et al. 2022)	95.1
Proposed CornealVisioNet	99.85

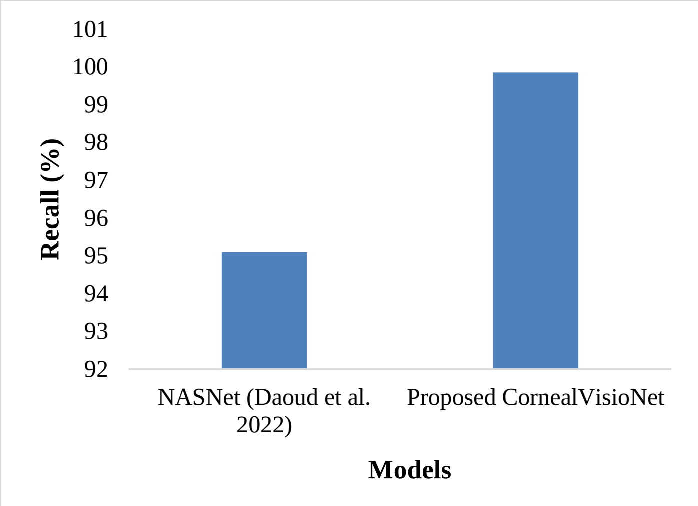


Fig 15. Grade Recall of proposed and existing models

7.4 F1 Score of Proposed and Existing Models

The F1 score is a harmonious average of precision and recall, providing a balanced measure of model performance. The F1 scores for class, type, and class are notable, with values of 0.9722, 0.9926, and 0.9941, respectively. These scores demonstrate a high level of accuracy and reliability in predicting corneal ulcers of all types, grades, and grades.

Table 10 and Figure 16 presented the F1 Score of detection of category of corneal ulcers of existing NASNet and proposed CornealVisioNet. The proposed CornealVisioNet stands outstandingly attain F1 Score of 97.22%, signifying its exceptional ability to balance both precision and recall in the categorization of corneal ulcers. This high F1 Score indicates that Proposed CornealVisioNet can not only accurately classify ulcers but also efficiently retrieve relevant instances. This is particularly important in medical image analysis, where misclassifications and missed diagnoses can have severe consequences. In contrast, NASNet exhibits a lower F1 Score of 65.9%, indicating a potential imbalance between precision and recall, which suggests that while it may perform well in some aspects of categorization.

Fig 16. Category F1 Score of proposed and existing models

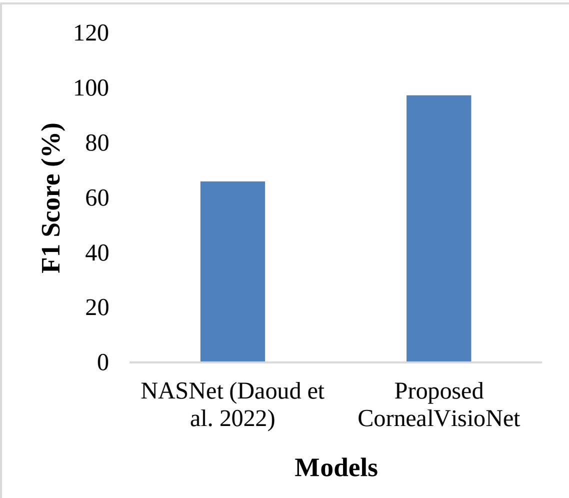


Table 10. Category F1 Score of proposed and existing models

Reference	F1 Score (%)
NASNet (Daoud et al. 2022)	65.9
Proposed CornealVisioNet	97.22

Table 11 and Figure 17 presented the F1 Score of detection of types of corneal ulcers of existing NASNet and proposed CornealVisioNet. The Proposed CornealVisioNet demonstrates an exceptional F1 Score of 99.26%, which signifies its outstanding ability to strike a proportion between precision and recall in the classification of corneal ulcer types. This high F1 Score suggests that Proposed CornealVisioNet excels in both the accurate identification and efficient retrieval of various ulcer types, which is crucial in medical image analysis for precise diagnosis and treatment. NASNet also exhibits a strong F1 Score of 95.7%, indicating commendable performance in categorizing ulcer types. However, it falls slightly behind Proposed CornealVisioNet, suggesting potential areas for improvement in terms of achieving a more optimal balance between precision and recall. The Modified VGG network, with an F1 Score of 71.39%, performs reasonably well but lags significantly behind both NASNet and Proposed CornealVisioNet. The outstanding F1 Score achieved by Proposed CornealVisioNet underscores its potential as a powerful tool for healthcare professionals, offering a high level of confidence in the accurate and efficient categorization of corneal ulcer types, ultimately leading to improved patient care.

Table 11. Type F1 Score of proposed and existing models

Reference	F1 Score (%)
Modified VGG network (Tang et al. 2020)	71.39
NASNet (Daoud et al. 2022)	95.7
Proposed CornealVisioNet	99.26

Fig 17. Type F1 Score of Proposed and Existing Models

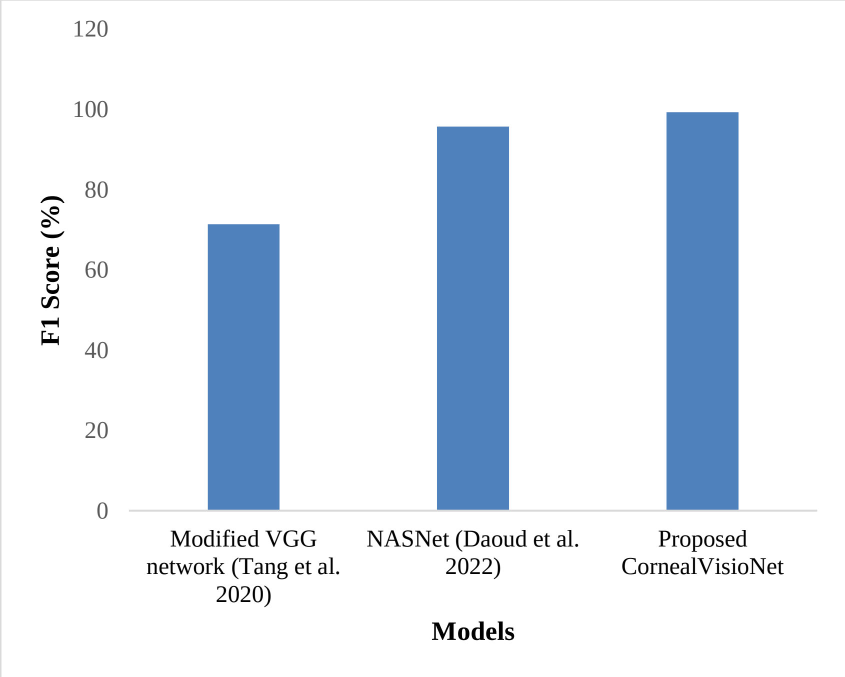


Table 12 and Figure 18 presented the F1 Score of detection of grade or severity of corneal ulcers of existing DCNN, NASNet, and Proposed CornealVisioNet. The proposed CornealVisioNet stands out impressively with an exceptional F1 Score of 99.41%, signifying its remarkable ability to balance precision and recall in grading corneal ulcers accurately. This high F1 Score implies that proposed CornealVisioNet not only excels in identifying different ulcer grades but also efficiently retrieves relevant instances, crucial for clinical decision-making. The NASNet follows closely with an F1 score of 95.1% demonstrating strong performance in grading ulcer severity. The DCNN also performs well with an F1 Score of 95.04%. The high F1 Score achieved by Proposed CornealVisioNet underscores its potential as a valuable tool for healthcare professionals, offering a high degree of confidence in precise grading of corneal ulcers, ultimately leading to more accurate treatment decisions and improved patient outcomes.

Reference	F1 Score (%)
DCNN (Teeyapan, 2021)	95.04
NASNet (Daoud et al. 2022)	95.1
Proposed CornealVisioNet	99.41

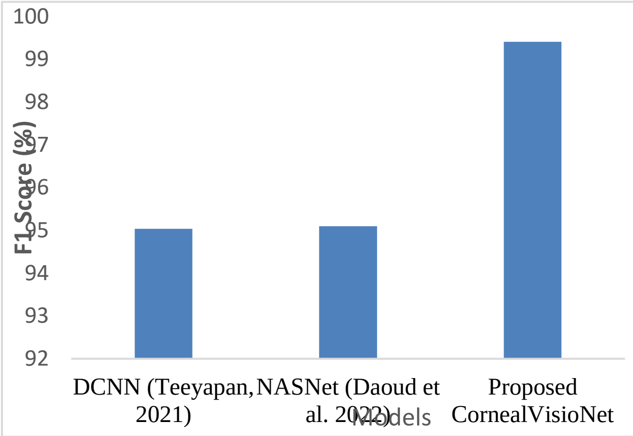


Fig 18. Grade F1 Score of proposed and existing models

3. CONCLUSIONS

The performance analysis of the proposed model showcases its effectiveness in accurately predicting corneal ulcer characteristics. The high accuracy, precision, recall, and F1 scores obtained across all categories, types, and grades highlight the model's robustness and reliability. These results demonstrate the potential of the proposed model to assist clinicians in diagnosing and treating corneal ulcers, ultimately leading to improved patient outcomes. The various conclusions as derived from this study are as follows;

1. The proposed CornealVisioNet achieved impressive accuracy scores across all categories, types, and grades of corneal ulcers, highlighting its robustness in correctly classifying these ulcers.
2. The category accuracy of Proposed CornealVisioNet model was 11.1% and 24.9% higher than the existing Resnet101 and NASNet model
3. The model exhibited excellent precision scores in identifying categories, types, and grades of corneal ulcers, indicating its ability to make accurate positive predictions.
4. The proposed CornealVisioNet demonstrated superior precision compared to NASNet in category classification, which is essential for minimizing misclassifications in medical image analysis.
5. The recall scores for the proposed CornealVisioNet were exceptional, indicating its effectiveness in retrieving instances of corneal ulcers across categories, types and grades. It significantly outperformed NASNet in category, type, and grade recall, emphasizing its comprehensive and reliable detection capabilities.
6. The F1 scores for the proposed model were remarkable, demonstrating a harmonious balance between precision and recall across all corneal ulcer categories, types and grades.
7. It was concluded that the proposed CornealVisioNet outperformed existing models such as Resnet101, DCNN, Modified VGG network, ResNet101 with PCA and NASNet making it a powerful tool for precise categorization in clinical practice.

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