Multi Categorical of Common Eye Disease Detect Using Convolutional Neural Network: A Transfer Learning Approach

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APPROVAL

This thesis titled "**Multi Categorical of Common Eye Disease Detect Using Convolutional Neural Network: A Transfer Learning Approach**" submitted by **Abu Kowshir Bitto**, **ID: 181-35-2379** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Software Engineering (SWE) and approved as to its style and contents.

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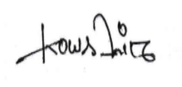
I hereby state that I have taken this thesis under the supervision of **Dr. Imran Mahmud, Associate Professor, Department of Software Engineering, Daffodil International University.** I also acknowledge that neither this thesis nor any part of this has been submitted elsewhere for the award of any degree previously by others.



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ABSTRACT

The eye is one of the most vital organs in the human body. Humans, despite their diminutive stature, are unable to see life without it. A thin covering known as the conjunctiva protects the human eye from dust particles. It works as a lubricant in the eye, preventing friction during the eye's opening and closing. There are various different types of eye ailments. Because the human eye is the most important of the four sense organs, it is necessary to detect external eye diseases early. Pattern recognition can be applied to a wide range of scenarios. One of these apps is a medical application. In this paper we use Convolutional Neural Network different architecture to detect normal eyes, conjunctivitis eyes and cataract eyes where apply ResNet50, VGG 16 and Inception v3. Among them ResNet50 performs 99 percent accuracy to detect eye disease with 485s time taken to detect. Respectively, Inception v3 performs 97 percent accuracy and VGG16 performs 95 percent accuracy.

Keywords: Eye Disease, Transfer Learning, VGG16, ResNet50, Inception v3

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

According to world health organization around the world, 2.2 billion people suffer from vision problems. One of the most important organs in the human body is the eye. Humans, despite their small stature, are unable to see the life around them without it. The human eye is shielded against dust particles by a thin coating known as the conjunctiva. It acts as a lubricant in the eye, preventing any friction during the opening and shutting of the eye. The white part of the eye, commonly known as the sclera, turns red due to the dilatation of blood vessels [11]. There are several eye diseases. The human eye is the most essential of the four sense organs, early identification of external eye disorders is critical. Pattern recognition may be used in a variety of situations. A medical application is one of these applications. Several studies were done in order to classify one or more eye disorders, with varying levels of accuracy attained depending on the preprocessing and classification approaches utilized [14]. The human eye is a light-sensitive organ that permits vision. Photoreceptive cells in the retina, such as rod and cone cells, are able to detect visible light and transmit this information to the brain. The brain uses information from the eyes to generate perceptions of color, shape, depth, movement, and other characteristics. The sensory nerve system includes the eye.

Conjunctivitis is one kind of eye disease. Conjunctivitis, often known as pinkeye, is a condition in which the conjunctiva becomes inflamed. The conjunctiva is a thin, transparent tissue that borders the inside of the eyelid and covers the white portion of the eye. It's a common occurrence among children. It's very infectious, although it's seldom fatal. It's quite improbable that it'll harm your eyesight. Viral conjunctivitis, bacterial conjunctivitis, and allergic conjunctivitis are the three most common conjunctivitis. Each type of conjunctivitis has its own set of symptoms. As viral conjunctivitis can develop alongside the symptoms of a cold, flu, or other respiratory infection, it is important to get medical attention as soon as possible. It usually starts in one eye and spreads to the other within a few days. Bacterial conjunctivitis is frequently coupled with discharge (pus), which can cause the eyelids to cling together. This might happen when you have an ear infection. The most prevalent anterior inflammatory diseases of the eye are allergic conjunctivitis [2]. Allergic conjunctivitis is a kind of allergic conjunctivitis that affects both eyes. Itching, weeping, and swelling of the eyes are possible side effects. Allergy symptoms, such as a runny nose, sneezing, a scratchy throat, or asthma, may develop.

Cataract is one of the eye diseases. Cataract is a clouding of the lens of the eye that is the main cause of blindness and visual loss globally. A cataract is a clouding of the lens of the eye, which is typically clear. The majority of cataracts grow slowly and do not affect vision at first. Cataracts, on the other hand, will ultimately obstruct eyesight. Cataract eyes have a few signs and symptoms. Increasing trouble with eyesight at night, clouded, blurred, or dim vision, light sensitivity and glare, Color fading or yellowing, Double vision in one eye, for example. The cloudiness induced by a cataract may only damage a tiny portion of the eye's lens, leaving the patient oblivious of any visual loss. The cataract increases in size, clouding the lens and distorting the light flowing through it.

Eye disease is a prevalent health problem that affects people all over the world. Cataract and conjunctivitis are two such disorders. Scientists are now concentrating their efforts on employing image processing to diagnose specific eye ailments. Conjunctivitis is an important eye infection to watch out for among these disorders. as well as being diagnosed Eyesight is one of most essential senses: we perceive 80 percent of what we see with our eyes. Healthy brain function need good vision. The brain is the most important organ in our bodies, allowing us to live complicated lives. Because your optic nerve connects your eyes and your brain, you'll need a healthy co-dependent connection. You keep your brain healthy by keeping your eyes healthy, which improves your entire quality of life. Increased athletic abilities, better driving skills, improved learning and understanding, and a higher quality of life are all benefits of good eyesight. So it’s important to identify eye diseases as early as possible. In this paper we will use Convolutional Neural Network different architecture to detect normal eyes, conjunctivitis eyes and cataract eyes with 2250 eyes data individually 750 for normal eyes, 750 for conjunctivitis eyes and 750 for cataract eyes.

1.2 RESEACRH OBJECTIVES

- Detect Eye Disease using Multi Class.
- Focusing on Most Common and Harmful Eyes.
- Eyes disease detect using Deep Learning Models.
- Implement with Own Data Collection.
- Comparing the Best Model.

1.3 RESEARCH GAPS

- Everyone just utilized with a little amount of data. (Example: 200,370,590,600)
- More data can predict accurate results.
- No one has yet compared the ability of different deep learning architecture to detect many levels of disease.
- No one applies new pre trained models with time finding.

1.4 ORGANIZATIONS OF THESIS

- Chapter 1: Chapter one produces the introduction of the thesis. Here also describe the research objectives and the research question.
- Chapter 2: This chapter describes the background, literature review and demonstrates previous work related to this study.
- Chapter 3: This chapter depicts the whole proposed model and architecture.
- Chapter 4: This chapter presents the experiment and result and evaluation of the studies.
- Chapter 5: This chapter concludes with future scope and limitations.

CHAPTER 2
LITERATURE REVIEW

2.1 LITERATURE REVIEW

A number of papers, research, and scientific papers on eye disease have already been published by a group of writers. To go along with our work, we've included some work reviews below.

Hartmann, Anja et al. [1] worked with multiplex real-time polymerase chain reaction for FHV and C felis, nested polymerase chain reaction and BLAST sequencing for mycoplasma species, immunofluorescent assay, and statistics A total of forty-one cats took part in the investigation. They came from private houses (nine cats; 22%), animal shelters (20 cats; 49%), and farms (nine cats; 22%). (nine cats; 22 percent). (12 cats, or 29% of the total). The severity of conjunctivitis was scored on a scale of 0 to 4 on a range of 0 to 4. All cats were clinically evaluated by the same examiner, and the severity of conjunctivitis was graded on a scale of 0 to 4 on a range of 0 to 4. There were a total of 41 cats, with 37 of them having an ocular pathogen. Single and multiple infections were discovered in 15 and 22 cats, respectively. FHV, mycoplasmas, and C felis were detected by PCR in 11 (27%) cats, 20 (49%) cats, and 23 (56%) cats, respectively. Ten cats were found to be C felis positive by the IFA. Mycoplasma felis, Mycoplasma canadense, Mycoplasma cynos, Mycoplasma gateae, Mycoplasma lipophilum, and Mycoplasma hyopharyngis were discovered using genetic sequencing. The virulence of these species in cats with conjunctivitis is uncertain, and more research is needed to determine their pathogenicity.

Hom, Milton et al. [2] analysis pearson x2 tests, binary logistic regression. A total of 689 patients from an ambulatory care center were chosen at random. Patients at optometric offices had their itchiness, dryness, and redness levels categorized based on their ocular history and itchiness, dryness, and redness levels. 194 (28.2%) of the 689 people tested had clinically significant itching, 247 (35.8%) had dry eyes, and 194 (28.2%) had redness (28.2 percent). Of the 194 people who had itching, 112 (57.7%) also had clinically significant dryness. Of the 247 people with dry eyes, 112 (45.3%) experienced clinically severe irritation. Redness was present in 120 of the 194 patients with itch (61.9%) and 122 of the 247 patients with dryness (49.4 percent). According to statistical analysis, self-reported itching, dryness, and redness were not independent of one another.

Sambursky, Robert et al. [3] work with RPS Adeno Detector, immunofluorescence staining for confirmation, and polymerase chain reaction. After developing a red eye and being diagnosed with acute conjunctivitis, 186 people from five clinical locations sought treatment within one week. When compared to CC-IFA, the RPS Adeno Detector was 88 percent sensitive and 91 percent specific in diagnosing adenoviral conjunctivitis. The RPS Adeno Detector's sensitivity increased to 89 percent and its specificity to 94 percent when using PCR as a reference procedure. The CC-IFA method was shown to be 91% more sensitive and 100% more specific than PCR.

Triwijoyo, Bambang et al. [4] apply convolutional neural network apply on STARE, which contains 400 retinal color photographs in 24-bit RGB format with a resolution of 605 * 700 pixels. An ophthalmologist evaluated 200 retinal imaging files. The classification of retinal images will be aided by powerful classifiers. According to our experiments, input images with size of 61*71 and 31*35 pixels produce the best training accuracy. According to the network configuration used, the highest test accuracy of the input picture with the lowest resolution of 31*35 pixels is 80.93 percent. The next step in the research is to learn more about the many CNN configurations that can be utilized to boost accuracy, such as choosing training methods for fully connected layers and using ensemble learning machines.

Arthur, Fourcade et al. [5] provide a systematic review of studies published in the medical literature before May 2019 that used CNNs for medical image analysis. In the PubMed database, 352 articles were found, with 327 being excluded. The authors were mostly from North America and Asia. Large amounts of high-quality medical images were needed to train the CNNs, which were often collected through international collaboration. The most extensively used CNNs, such as AlexNet and GoogleNet, which were designed for natural image processing, have proven to be useful for medical imaging. CNNs will not be able to replace medical doctors, but they will aid in the improvement of routine tasks and so have a positive impact on our profession.

Li, Wei et al. [6] used Convolutional Neural Network and an auto-encoder model. There are two groups in the conjunctivitis dataset. There are 626 photographs in the first group, including 464 healthy images (230 HR and 236 H) and 197 sick images. The second set has 150 photographs, including 100 healthy (50 HR and 50 H) and 50 sick (50 HR and 50 H) images. To improve classification accuracy, researchers proposed an AE-based classification technique and investigated the impact of different loss functions on Convolutional Neural Network classification accuracy. Because just a few studies have looked at how to estimate the number of hidden nodes inside the latent compressed vector, we investigated the impact of different numbers of hidden nodes on classification performance.

Sibitz, Christina et al. [7] analysis Ophthalmology, Chlamydiaceae RT PCR, Chlamydiales PCR. A total of 74 cats were used in the study. They were divided into two groups: 49 cats with conjunctivitis (K1 to K51; two cats were retroactively eliminated due to slight eye symptoms, but the initial nomination was maintained) and 25 cats with no clinical eye or upper respiratory tract symptoms (K1 to K25) (designated G1 to G25). This study is the first to detect the identified human pathogen C. pneumoniae in feline conjunctivitis patients using Chlamydiaceae RT PCR and sequence analysis. Using Chlamydiaceae RT PCR and subsequent sequence analysis, C. pneumoniae was found in five cats in the conjunctivitis group. Chlamydophila felis was discovered in two cats with conjunctivitis.

Prentice MJ et al. [8] done analytical statistics. Samples were taken from both eyes of 104 babies with conjunctivitis and either the left or right eye of 104 controls, with the side sampled matching that of the conjunctivitis-affected baby. Neonatal conjunctivitis was observed to occur 8.2% of the time, and no neomycin-resistant disease was discovered during the study. Staphylococcus aureus, viridans Streptococci, and Eschlerichia coli were the only bacteria found in significantly higher numbers in afflicted eyes than in control eyes, suggesting that these bacteria may be the cause of conjunctivitis. In all cultures, Chlamydiae, M. hominis, Neisseria gonorrhoeae, and anaerobic bacteria were confirmed to be negative. The frequency of conjunctivitis, the time it took to manifest, or the microorganisms found had no effect on the mother's race, socioeconomic status, illness, or obstetric events.

M. Gaubatz et al. [9] work with face detection, red-eye detection, and red-eye correction. On a batch of 200 photographs with persons in them, this strategy was put to the test. The technique was able to eradicate roughly 95% of the undesirable red-eye artifacts in the test bed. On a computer with a 1 GHz CPU, a 1-megabyte image takes many seconds to fix. The face detector only found one false positive non-face, whereas the red-eye detector found no red-eye in this non-face region. Furthermore, the red-eye detector produced only one false positive red-eye detection.

Jian Wan et al. [10] used Model of Active Appearance (AAM). A collection of 300 faceless consumer photos. The technology properly identified roughly 98 percent of the red-eye anomalies in the test samples. The algorithm missed the majority of the artifacts since the red-eyes were not visible to the naked eye. The technique uses both low-level red-eye characteristics and a template-based approach to detect red-eyes in consumer images. It has a high level of resiliency, allowing it to detect the majority of redeyes in a range of situations.

Verma, Sherry et al. [11] appluy convolutional neural. This study used twenty-eight photographs of bulbar redness and twenty-eight photographs of healthy eyes. The primary purpose of this study was to develop a CNN-based classifier that could distinguish between a healthy and a red human eye in the shortest time possible. Healthy eyes have a classification accuracy of 94.17, while red eyes have a classification accuracy of 99.99.

Wang, H. et al. [12] used coherent imaging, deep neural networks with 965 colonies from 15 plates that were not presented during the network training or validation stages were used to blindly assess the system's performance in early detection of bacterial colonies. The presented method may detect bacterial growth as early as 3 h and detect 90% of bacterial colonies within 7–10 h (and >95 percent within 12 h) with a precision of 99.2–100%. The technique correctly identifies 80 percent of all studied bacterial colonies for K. pneumoniae, E. coli, and K. aerogenes within 7.6, 8.8, and 12 hours, respectively. These results reveal a total time savings of more than 12 hours when compared to gold-standard techniques (e.g., Colilert test and Standard Method 9222B), which take 18–24 hours.

Ş. Karahan et al. [13] apply Haar algorithm, deep neural network. There are 16K positive and 52K negative image patches in all. The approach has a higher recall value than the Haar algorithm on both the FDDB and CACD datasets. According to the accuracy rate, the Haar approach, on the other hand, is successful on the FDDB dataset.

Ahmed Salman et al. [14] work with back propagation with a parabola function based on a linear cyclic learning rate. https://www.shutterstock.com/ was used to gather 590 samples. There are seven diseases that affect the eyes in addition to the normal eye. Back propagation with a linear cyclic learning rate-based parabola function is used in this article to diagnose seven external eye illnesses as well as the normal eye. This article's categorization accuracy is excellent (89.83 percent).

S. K. Sundararajan [15] apply deep-learning convolution neural network, fuzzy segmentation technique on Photographs (600) Initially, the value for 1500 was increased in data set two, and then the value for 100 images was increased in data set three. When the DLCNN approach is applied to the medical field, it yields excellent results. With such a high value discrepancy between train and test accuracy, an overfitting problem arises. However, when the data augmentation technique was applied in the model for data set 2, the data fitting difficulty was minimized, and the value difference was considerably smaller, and the same is true for data set 3.

Malik, S. et al. [16] apply Neural Network, Decision Tree, Nave Bayes, Random Forest in the data include age, disease history, and clinical observations. This data was categorized using medical experts' hierarchical hierarchies, and diagnoses were generated using the American Academy of Ophthalmology's ICD-10 coding system. The system is designed to expand through self-learning by introducing new categories for both diagnosis and symptoms. The results of the classification using tree-based algorithms revealed that, given enough data, the proposed framework works well. Because of the organized data organization, the prediction rate of the random forest and decision tree algorithms is over 90% when compared to more advanced approaches such as neural networks and the naive Bayes algorithm.

Masumoto, Hiroki et al. [17] worked with DenseNet201, DenseNet121, VGG19, ResNet50, InceptionV3, Xception, Inception, and ResNetV2 model, the training data was 3700 images, and the validation test data was 923 images. With 3,700 photos, the neural network was trained to grade conjunctival hyperaemia using the JOAS technique. We used 923 additional shots as validation test images to see how accurate the algorithm was at grading. choose the most efficient combination of these networks DenseNet201 was the best individual model, while the best model was a combination of DenseNet201, DenseNet121, VGG19, and ResNet50.) The correlation between multimodel responses and vessel-area occupied was 0.737 (p 0.01). This method would be as exact and thorough as professionals, but it would be significantly more efficient and consistent with objective criteria.

Manchalwar, Mrunalini et al. [18] used Oriented Gradient Histogram methods. Two images of cataracts, two images of conjunctivitis, and two images of normal eyes use for data. The suggested technique demonstrates how to use HOG to extract the best components from the pupil and sclera parts of the eye in order to diagnose cataract and conjunctivitis. They used HOG to extract features, and a minimal distance classifier was used to categorize the extracted features. Our algorithm clearly distinguishes between normal and cataract- and conjunctivitis-affected eyes. In the future, l focus on recognizing them. Additional eye problems include stye, subconjunctival hemorrhage, and chalazion.

L. Jain et al. [19] approach Convolutional Neural Network. The initial batch comes from Friedrich-Alexander University's machine learning data repository. A total of 15 healthy retinal fundus photographs were taken, as well as 30 ill retinal fundus images with a mix of diabetic retinopathy and glaucoma. The photographs were then improved to provide 1021 sick images and 522 healthy images. The second set came from a local eye clinic in Bangalore, India, that specialized in retinal problems. A fundus camera was used to take 800 photographs of sick (Diabetic Retinopathy) and healthy retinas. After then, 1680 images were created using lateral inversion and flipping. There were 960 photographs of illness and 720 photographs of health. We achieved average accuracy of 96.5 percent and 99.7 percent on such datasets.

Tsubota K et al. [20] propose Hansel's approach, often known as the cytologic method. The conjunctivas of 18 patients with vernal and allergic conjunctivitis and 10 patients who served as controls were scraped. Mast cells and eosinophils were found to be linked with early detection of allergic conjunctivitis, but not with clinical severity, as determined by our cytologic approach.

Y. Dong et al. [21] worked with the method of maximal entropy. Softmax Classifier, Convolutional Neural Network, Support Vector Machine Classifier Normal, mild, medium, and severe cataracts are categorized into four categories. The feature created using deep learning and classified by Softmax has a greater accuracy when compared to the classification results. Our deep learning research has shown to be both successful and valuable, as seen by the findings. On 7851 fundus photographs

M. Gunay et al. [22] apply Stochastic Gradient Descent, GrabCut, Gray-Level Co-occurrence Matrix. For the training set, used 18 healthy and 12 Ad-Cs eye pictures. Corneal images used with our basic setup and analyzed with the DIP approach proposed successfully detected and isolated possibly infectious patients. They are correct 93 percent of the time. Because of a mix of circumstances, we were able to achieve this rate. To isolate the sclera, an automated GrabCut approach was used. This sets the seed zone apart from the rest of the image. Such adaptability is rare. The difficulty caused by the brightness and clarity is addressed by the remoteness of the location of interest.

A. Bhadra et al. [23] used OpenCV approach developed with a dataset of 100 photos. The procedure of the suggested revolutionary strategy is implemented using the OpenCV library. In a variety of normal and ill eye images, pattern recognition along with the BGR color feature is used to try to detect cataract and conjunctivitis. Over a 100-image sample, the results reveal an average accuracy of 92 percent for cataracts and 83 percent for conjunctivitis. The accuracy of larger-scale tests can be increased even more by collecting additional dataset photographs.

Perdomo Charry et al. [24] worked with LeNet Convolutional Network. The database contains 315 photographs with sizes ranging from 1440 960 to 2540 1690 pixels, 268 images without a lesion, and 47 exudates that were segmented by ophthalmologists from the OPHDIAT Tele-medical network as part of a project funded by the French Research Agency (ANR). The e patches dataset comprises 20148 photos of 48 by 48 pixels, including 10074 healthy and 10074 exudate photographs, after cropping all of the Ophtha dataset pictures and data augmentation. When the learning rate was 0.01 and the batch size was 64, the proposed model performed best. The CNN model performs admirably when it comes to recognizing exudate in eye fundus images. This research gave encouraging early results in identifying exudate.

A.El-Hag et al. [25] work with Gauss gradients, fuzzy method, Convolutional Neural Network. The input images are taken from the Structured Analysis of the Retina (STARE), Digital Retinal Images for Vessel Extraction (DRIVE), High Resolution Fundus (HRF), and Digital Retinal Images for Optic Nerve Segmentation (DRIONS). A Convolutional Neural Network (CNN) is used to distinguish between normal and abnormal instances. In retinal image classification, fuzzy preprocessing is used to improve the original image and increase the contrast between the objects and the background. Binarization separates both blood vessels and the optic disc from the original image, which are then deleted during image segmentation. Following this method, the retinal image is subjected to a gradient approach in order to differentiate between normal and diseased cases.

P. Chakraborty et al. [26] use Convolutional Neural Networks (CNNs), Optical Coherence Tomography (OCT) and chest X-ray photographs of 1-5 year-old children are assessed and used as inputs. The eye dataset has a validation accuracy of around 90%, while the lung dataset has a validation accuracy of around 63 percent. The proposed method aims to aid medical practitioners in making more accurate diagnoses, reducing infant mortality from pneumonia and allowing for early detection of the severity of eye disease.

Tahira Nazir et al. [27] used Mask RCNN and Densenet-77 methods. In the system's evaluation testing, the ORIGA "Online Retinal Fundus Image Database for Glaucoma Analysis" dataset was employed. The "Eye Research Institute, Singapore" provided the collection, which has 650 images, including 168 glaucomatous samples and 482 no glaucomatous samples. At the feature extraction level of Mask-RCNN, the Densenet-77 framework is employed to compute the deep key points. Finally, the calculated features are used by the custom Mask-RCNN model to localize and segment the OD and OC. The proposed framework's accuracy, recall, F-measure, and IOU were 0.965, 0.963, 0.97, and 0.972, respectively. When compared to current approaches, demonstrated remarkable performance in terms of both efficiency and efficacy in the face of blurring, noise, and light variations.

M. S. A. Vigil et al. [28] apply YOLO V2, R-CNN, WordTree, ImageNet, and COCO are some of the algorithms used. There are 9418 classes in the wordtree dataset. The total number of classes in the Imgenet release is 9000. We expect the Face detection dataset to be in the same format as the COCO Dataset as a result of integrating the datasets, allowing YOLO to use ImageNet to gain faster results in face detection and identification. Compare YOLO and R-GPU CNN's usage, as well as the time and frequency with which the DPM and engine are used. We compare the average mAPs of both engines in light of their distinct recognition frameworks to assess their speed and accuracy. With a mAP of 53%, it is twice as fast as any other known model for object detection. Using 63 percent, YOLO keeps up with the pace.

K. Prasad et al. [29] Develop a graphical user interface for convolutional neural networks (CNN). The Glaucoma datasets were got from Medimrg, while the DR dataset was obtained from Kaggle. The recommended approach can diagnose Diabetic Retinopathy and Glaucoma early. This method primarily serves as a referral trigger, telling the patient that if a positive result is detected, a retinal expert should be visited. The less complex pre-trained model is evaluated using a test set and real-time images. The rate of accuracy was set at 80%. Using parameter tuning and cross-validation procedures, this accuracy can be improved even more.

K. Nsaif et al. [30] used ResNet-50, faster R-CNN, Gabor filters, and a naive Bayes model. In an open dataset (CASIA-Iris-Distance database, Version 4.0), there are 2,567 UV photos of 142 people with varied degrees of reflection or blocking by glass. The training dataset included 111 images, whereas the test dataset included the remaining images. This research developed a more accurate eye identification model that is unaffected by occlusion or reflection from spectacles. A method for detecting the eye has been proposed. Experiments on the recommended FRCNN-GNB eye detection approach on the CASIA-IrisV4 database show that the accuracy in terms of eye detection is 100 percent. The results of the investigation reveal that the suggested treatment is effective.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 METHODOLOGY MODEL

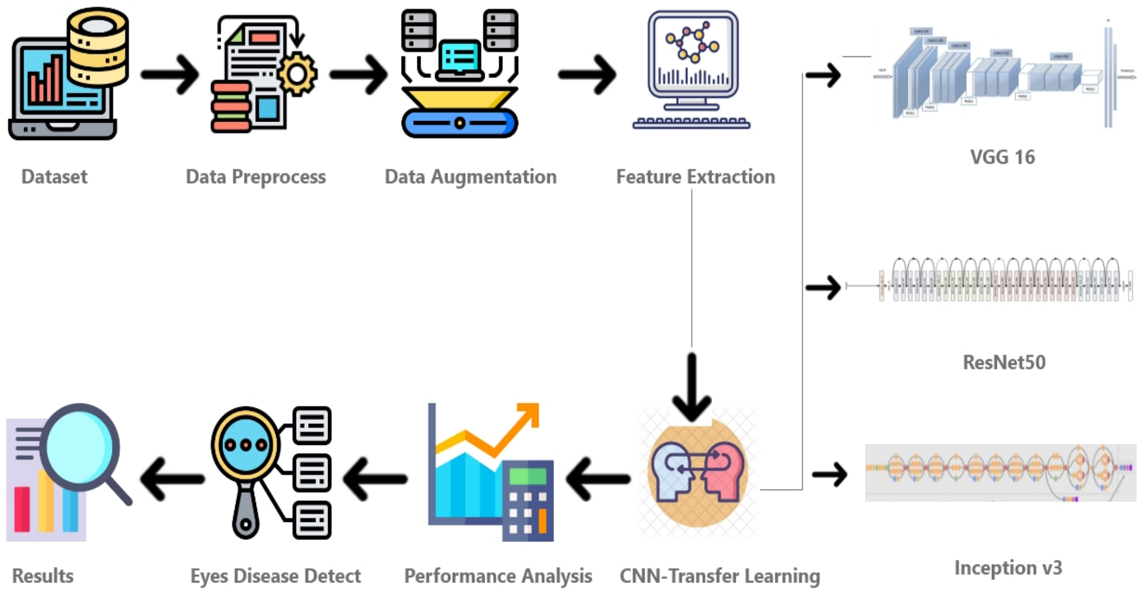

Figure: 3.1.1 Methodology Model

3.2 DATASET

It is impossible to overestimate the relevance of datasets in machine learning research [31]. Datasets have long been seen as a stumbling block to algorithmic development and scientific advancement. The type of competent and meticulous human annotation used in dataset gathering techniques in previous periods was shunned as the machine learning industry progressively shifted to data-driven methodologies. as ‘slow and costly to acquire,' and a shift toward unrestricted gathering of ever-larger amounts of data The use of large volumes of data from the internet, as well as a greater dependence on non-expert crowd workers, was seen. Machine learning will benefit from this. The data-driven turn in AI research, which has put large-scale datasets at the center of model development and evaluation, necessitates a careful, critical examination of datasets and dataset creation and use practices. As systems trained in this manner are deployed in real-world contexts that affect the lives and livelihoods of real people, it is critical that researchers, advocacy groups, and other stakeholders review the datasets and dataset creation and use practices.

In recent years, a number of issues have been raised about dataset collecting, annotation, and documentation procedures. We collect data from shutter stock and google website. Collect 2250 eyes data individually 750 for normal eyes, 750 for conjunctivitis eyes and 750 for cataract eyes.

3.3 PRE-PROCESSING

Picture preprocessing improves the efficacy of the image data required for image classification. Geometric alterations are used in preprocessing procedures. Rotation, scaling, and translation of images are all examples of image manipulation. We lowered the resolution of the data during the preparation stages. all photos to 224*224 pixels for VGG16 and 224*224 pixels for ResNet50, and 224*224 pixels for Inception v3. It must verify that all of the requirements are met. The photos are of the same high quality. For a quick image You'll need to label or categorize images utilizing a search engine. lookup by keyword at this moment, all of the transcribed photos had been saved. The dataset has been withdrawn. It aids in avoiding the problem of overfitting during the training procedure. When a network learns the data rather than the overall pattern of a dataset, it is said to be overfitting. The photos were augmented by applying specific image changes such as rotation, width shift, height shift, shear range, and horizontal flip to them.

3.4 DATA VISUALIZATION

During the experimentation, the dataset was taken into consideration. The customized eye disease dataset contains 2250 photos, 1689 of which are for training and the remaining 561 for testing. Many difficulties arose during the data collection process. Colors are added to the photographs that have been collected.

3.4.1 Cataract Eyes

3.4.2 Conjunctivitis Eyes

3.4.3 Normal Eyes

3.5 MODEL DESCRIPTION

1) Retraining a model: Assume that if we want to finish goal 'one' but don't have enough data to train a deep neural network, we should look for a task 'two' that is similar. That is correct. Use the model as a jumping off point for solving problems. After training it on 'two,' it faces new hurdles.

2) Using a Pre-Trained Model: The second alternative is to use a pre-trained model. There are several models available; however, how many layers to adopt and how many retraining to perform depends on the situation. Keras, for example, has nine pre-trained models for computer vision tasks, transfer learning, forecasting, feature extraction, and fine-tuning. In all of these models, we used three pre-trained models: VGG16, ResNet50, and Inception V3. Deep learning is the most common use of this type of transfer learning.

3) Transfer Learning (TL): TL [33] is the technique of transferring information from one domain to another. alternative for feature extraction and categorization TL stands for carried out with the use of a deep CNN model [16] that has been In terms of deep learning, it had already been trained on a large dataset. Because fine-tuning a CNN model that has already been trained is usually faster, considerably less time-consuming than training a CNN model with random data TL has recently been updated to include weights that have been initialized from the start. Many deep learning applications use it [34], [35]. The CNN models' initial layers learn characteristics such as edges, the former levels have curves, corners, and color blobs, whereas the latter levels have curves, corners, and color blobs. represent both abstract and specific characteristics. In reality, implementations, softmax layer, fully connected layer and the pre-trained CNN model's categorization output layer.

4) Visual Geometry Group (VGG16): Karen Simonyan and Andrew Zisserman [36] proposed Visual Geometry Group (VGG16), an excellent 16-layer deep vision neural network model. The network receives a two-dimensional image as input (224, 224, 3). The padding on the first two levels is the same, and the first two layers have 64 channels of 33 filter size. After that, there are two layers of 256 filter size and filter size convolution layers, followed by a stride (2, 2) max pool layer (3, 3). A stride (2, 2) max pooling layer follows, which is identical to the one before it. There are 256 filters in total, as well as two convolution layers with three and three filter sizes. Following that, there are two sets of three convolution layers, as well as a max pool layer. The image is then transformed into a two-layer convolution stack. Instead of 1111 filters in AlexNet and 77 percent in ZF-Net, we use 33 filters in these convolution and max pooling layers. In some of the layers, 11 pixels are also used to control the number of input channels. After each convolution layer, 1-pixel padding (the same padding) is added to avoid the spatial information in the image from being lost.

5) Residual Networks (ResNet50): A 50-layer convolutional neural network, Residual Network (ResNet50) [37]. ResNet50 is a 48-layer Residual Network with one Maxpool layer and one

Average Pool layer. Each of the ResNet-50 model's five phases has its own convolution and identity block. There are three convolution layers in each convolution block, and three convolution layers in each identity block. There are around 23 million trainable parameters in the ResNet-50.

6) Inception v3: Inception v3 is a convolutional neural network that was developed as a Googlenet module to aid in picture processing and object detection. It's the third version of Google's Inception Convolutional Neural Network, which was first shown off at the ImageNet Recognition Challenge. Inceptionv3 was created with the goal of allowing deeper networks while keeping the amount of parameters under control: it contains "under 25 million parameters," compared to 60 million for AlexNet.

CHAPTER 4
RESULT AND DISCUSSION

4.1 RESULT ANALYSIS

The 1689 training images and 561 validation images of eye disease were sorted into 80:10 groups. An Intel Core i5 processor and 8 GB of memory power the experiment platform. All input photos for the ResNet50, VGG16, and Inception v3 models were scaled to 224*224, 224*224, and 224*224 respectively. We used those applied models to scale photos to 224*224 in our experiment. Following that, the augmentation was completed. The weights of the pre-trained ResNet50 and VGG16 and Inception v3 models were employed.

In ResNet50 the adam optimizer was employed and a batch size of 64 and for loss function we used categorical cross entropy. The default variables for learning rate, decay, and momentum were used in this model. We were able to increase the amount of shots captured using this method, whereas most earlier efforts had less taken photos. We're trying to train our data using 5 epochs for ResNet50, with the goal of having those learning algorithms traverse through the entire training data set 20 times, respectively. Following the instruction, the testing time begins to verify correctness. Fig shows the training loss and validation loss and Fig shows the training accuracy and validation accuracy. ResNet50 performs 99 percent accuracy to detect eye disease image.

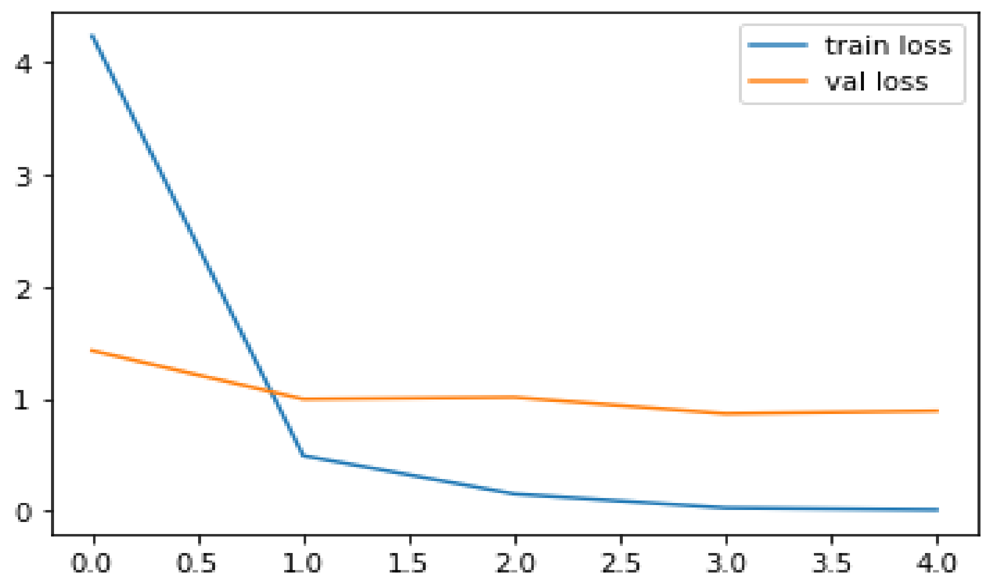

Figure 4.1.1 Training Loss Vs Validation Loss

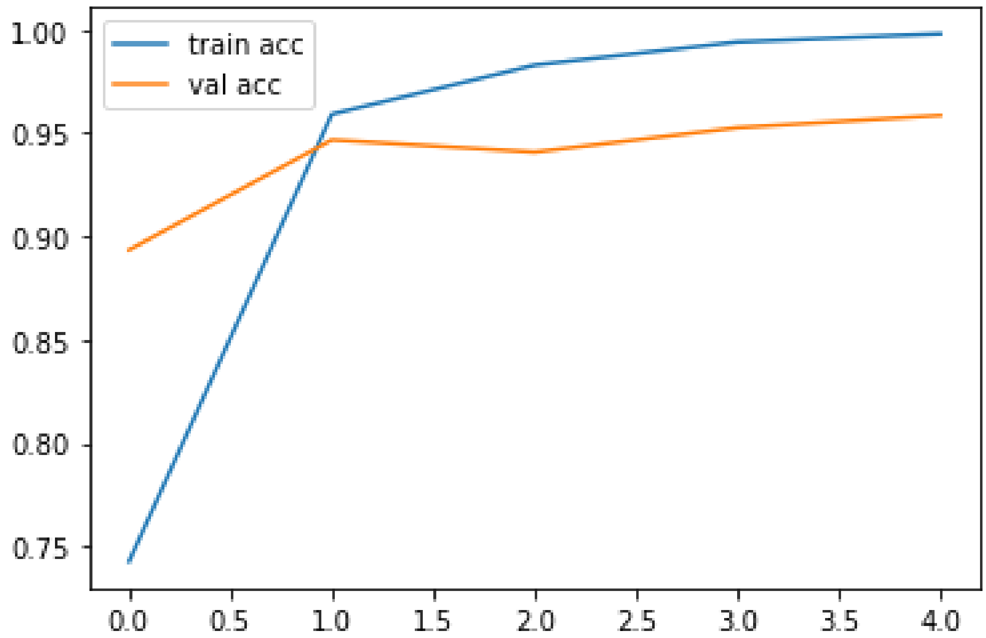

Figure 4.1.2 Training Accuracy Vs Validation Accuracy

In VGG 16 the adam optimizer was employed and a batch size of 32 and for loss function we used categorical cross entropy. In this model, the default values for learning rate, decay, and momentum were used. Using this strategy, we were able to increase the number of photographs captured, when most previous attempts had less photos taken. We're attempting to train our data with 5 epochs for VGG 16, with the goal of having those learning algorithms traverse the complete training data set 20 times. Following the instruction, the testing period begins to ensure that the instructions are followed correctly. Fig shows the training loss and validation loss and Fig shows the training accuracy and validation accuracy. VGG 16 performs 96 percent accuracy to detect eye disease image.

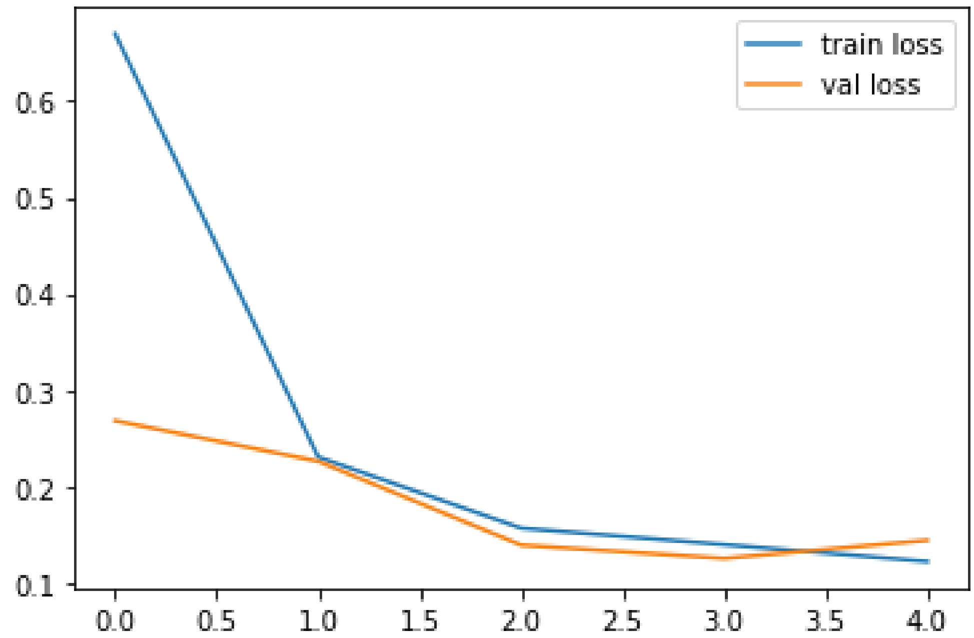

Figure 4.1.3 Training Loss Vs Validation Loss

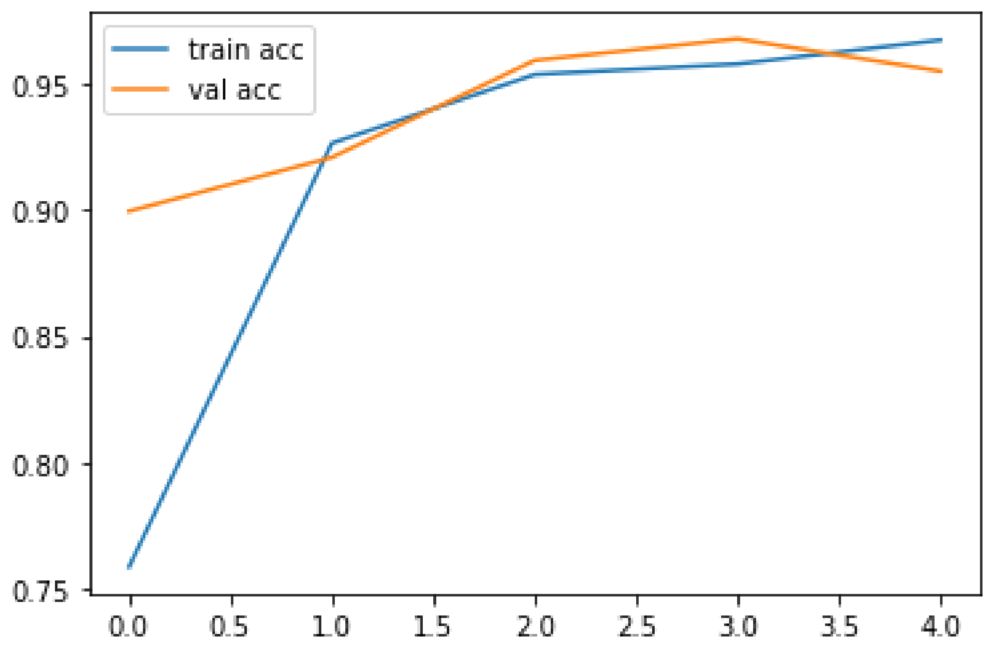

Figure 4.1.4 Training Accuracy Vs Validation Accuracy

In Inception v3 the adam optimizer was employed and a batch size of 32 and for loss function we used categorical cross entropy. In this model, the default values for learning rate, decay, and momentum were used. Using this strategy, we were able to increase the number of photographs captured, when most previous attempts had less photos taken. For Inception v3, we're attempting to train our data using 5 epochs, with the goal of having those learning algorithms explore the complete training data set 20 times each. Following the instruction, the testing period begins to ensure that the instructions are followed correctly. Fig shows the training loss and validation loss and Fig shows the training accuracy and validation accuracy. Inception v3 performs 95 percent accuracy to detect eye disease image.

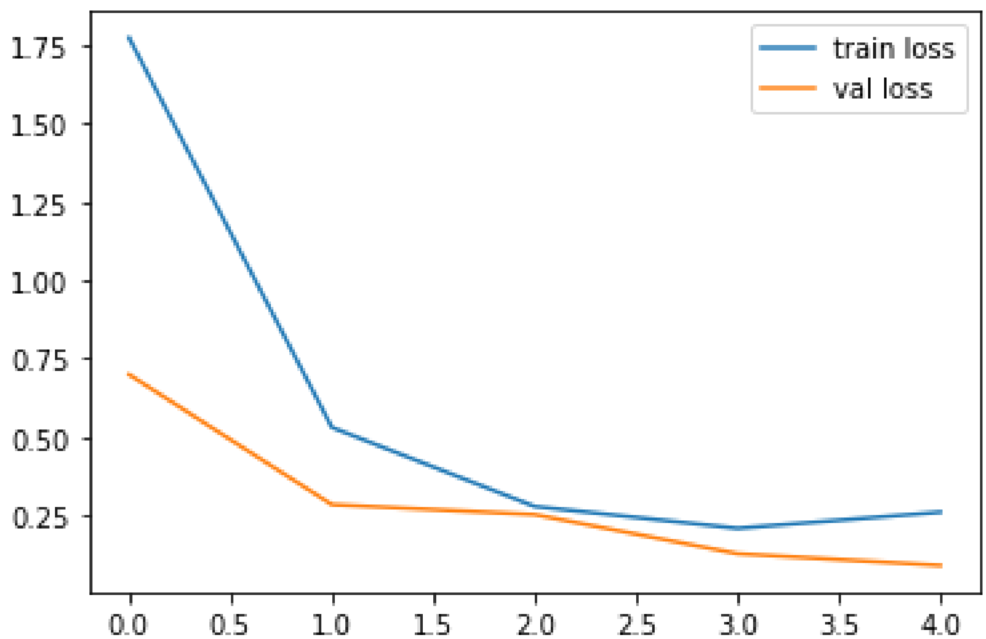

Figure 4.1.5 Training Loss Vs Validation Loss

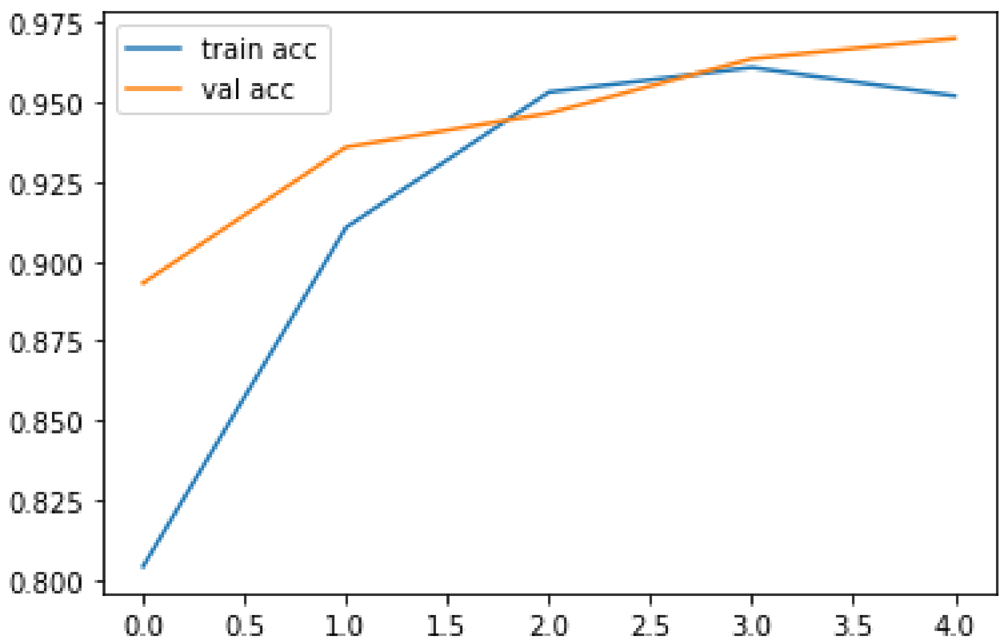

Figure 4.1.6 Training Accuracy Vs Validation Accuracy

Models	Loss	Accuracy	Validation Loss	Validation Accuracy	Time(s)
ResNet50	0.0084	0.9980	0.8900	0.9586	485
VGG 16	0.1321	0.9604	0.1439	0.9551	2510
Inception v3	0.2155	0.9568	0.0881	0.9701	1090

Table 4.1.1 Performance Table

In this suggested work, we are attempting to evaluate the newly trained model using the test data set. The training dataset, which included both the original and enhanced photos, was provided to our model as an option for continuing to train. The model was then verified in order to improve its comprehensiveness. The model's performance was evaluated using test photographs after it was trained on the eye disease dataset using the ResNet50, VGG16 and Inception v3 architecture. The weights of the pre-trained ResNet50, VGG16 and Inception v3 models were experimented with.

This was done to see how our model stacked up against other well-known transfer learning pre-trained networks. We looked at which pre-trained network will fit this dataset the best. Three separate models, ResNet50, VGG16, and Inception v3 were examined. From Table4.1.1 we can see ResNet50 perform most accuracy 99 percent with less time 485s to detect eye disease. Inception v3 performs second highest accuracy with 97 percent with 1090s to detect eye disease. Lastly VGG 16 performs 95 percent accuracy with taken highest time 2510s to detect eye disease.

CHAPTER 5
CONCLUSION

5.1 FINDINGS AND CONTRIBUTIONS

This research describes the detection efforts of transfer learning and deep feature extraction on eye illness identification using images collected from all around the world. Deep feature extraction and transfer learning are performed using three popular deep CNN architectures: ResNet50, Vgg16, and Inception v3. The gathered dataset is preferable in experimental work because to the high quantity of example photographs. Among all the models ResNet50 performs highest accuracy with 99 percent and less time 485s to detect eye disease. In the future, we intend to use different CNN models to increase classification accuracy.

5.2 FUTURE WORK

Data augmentation for transfer learning will be handled in the future. This research relates to a future goal, such as developing a model that can detect eye disease in real time using YOLO. Our findings will aid the medical department in using the technology and detecting eye problems as fast as possible. Mobile devices nowadays offer us convenience and diversity in terms of use. As a result, smartphone cameras could be used to detect eye disease by gathering photographs and videos in a short amount of time, allowing doctors to quickly diagnose and classify eye disease. It will also have a good impact on the growth of a pleasant and secure lifestyle.

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