Development of Deep Learning Based Application System for the Classification of Farm Related Ocular Disease in Benue State

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ABSTRACT

Farm related ocular diseases constitute a major public health challenge among agricultural workers, particularly in developing regions where access to specialized eye care is limited. Ocular diseases such as cataract, glaucoma, and retinopathy are prevalent among farmers due to prolonged exposure to sunlight, dust, chemicals, and poor occupational safety practices. Despite the growing burden of these conditions, limited studies have explored the application of artificial intelligence–based diagnostic systems using localized data from Benue State, Nigeria. This study presents the development of a deep learning–based application system for the classification of farm related ocular diseases in Benue State. A total of 2,715 ocular images were collected from 85 subjects diagnosed with cataract, glaucoma, and retinopathy at Okida Eye Clinic, Otukpo. The dataset was augmented to improve class balance and diversity, and transfer learning was applied using a pre-trained AlexNet model with frozen convolutional layers. Model performance was evaluated using accuracy and loss metrics during training in a Python environment. The proposed model achieved a classification accuracy of 96.5% with loss values below 0.2, demonstrating strong learning capability and generalization. Comparative analysis with existing state-of-the-art models shows that the proposed approach performs competitively while benefiting from localized clinical data. The trained model was integrated into a software application and tested with real ocular images, yielding high confidence classification scores. The system is therefore recommended as a reliable decision-support tool for early detection and management of farm related ocular diseases in Benue State.

Keywords: Ocular disease, Deep learning, AlexNet, Cataract, Glaucoma, Retinopathy, Benue State

INTRODUCTION

Without doubt, Benue state (food basket of the nation) has been consistent in sustaining the availability of food in Nigeria. However, with this success story comes many sacrifices the farmers make to ensure food availability. Notably among these sacrifices is the inherent risk of ocular trauma faced by agricultural workers. Aghadoost (2014) underscores ocular disease's significant impact on vision impairment and its role as a leading cause of avoidable monocular blindness. Globally, Jac Okereke et al. (2021) estimate eye injuries affect over 1.6 million individuals, leading to various degrees of vision impairment. The severity of these injuries is exacerbated in developing nations, attributed to factors such as socioeconomic disparities and inadequate healthcare infrastructure (Jac Okereke et al., 2021).

Recent studies have categorized ocular injuries into open-globe and closed-globe types based on the Birmingham Eye Trauma Terminology system (BETTS), aiming to standardize injury classification (Shah et al., 2018). Understanding the mechanism and force of trauma, as emphasized by Bajwa (2018), aids in assessing the extent of ocular damage, which can range from contusions to serious conditions like retinal detachments and corneal lacerations (Mohseni et al., 2023). In Nigeria, ocular disease stems from diverse sources including domestic accidents, industrial mishaps, and rural hazards like farming and hunting (Kyari, 2015). Adepoju et al. (2014) highlight gender disparities and psychological implications of such trauma, particularly in domestic settings.

Chemical injuries are prevalent, but cases linked to blasts and explosions are also reported, impacting ocular structures such as the cornea and eyelids (Adelson et al., 2021).

The agricultural sector presents unique risks, with farm laborers exposed to various ocular hazards including chemicals, dust, and radiation (Ezinne et al., 2021). Pesticide exposure, in particular, poses significant risks, as do environmental conditions like airborne particles from farming operations (Thetkathuek et al., 2017). Sunlight exposure contributes to long-term ocular damage, with effects ranging from cataracts to retinal damage (Onyekwelu et al., 2019). Despite these risks, research on the ocular health of Nigerian farmers remains limited (Kulshrestha and Mishra, 2021). Understanding the critical role of vision in agricultural activities, this study aims to assess the ocular health and safety practices of farmers in rural Nigeria, employing deep learning techniques for the classification of farm-related ocular disease in Benue State.

Benue state is a region known for its rich practices in agriculture where a significant number of populations engage in farming activities. But it is unfortunate how the nature of the work exposes them to various occupational hazards such as ocular disease. The challenge of ocular disease worsens due to limited healthcare resources, delayed diagnosis and treatment, lack of awareness and data deficiency. These problems cause the affected population to suffer longer, have greater rates of morbidity, and have a higher chance of becoming blind. Furthermore, farmers and medical professionals are ignorant about the seriousness of ocular injuries and the value of prompt treatment. Inadequate information regarding the frequency and consequences of these injuries makes public health planning even more difficult.

To solve these issues, a deep learning-based system for categorizing ocular disease associated to farmers must be developed. By improving diagnostic precision, this technology can guarantee prompt medical intervention, support healthcare professionals in environments with limited resources, and give vital support. The approach can assist avoid eyesight loss and sustain worker productivity in the agriculture industry by enhancing care accessibility and raising awareness in the neighborhood. Additionally, by gathering and analyzing data on ocular desease incidences, public health policies and preventive measures can be improved, which will ultimately benefit Benue State's health and eye care standards. The contributions of this work are as follows;

i. To adopt a pre-trained model and fine-tune with localized ocular data and generate a model for ocular diseases classification

ii. To integrate the model as a software for the diagnosis of ocular related diseases

iii. To experimentally access the operational efficiency of the system developed using real- world test scenarios

LITERATURE REVIEW

Emem et al., (2021) researched on the cases of ocular toxoplasmosis among livestock farmers and raw meat handers. The purpose of this research was to ascertain the incidence of OT and other risk factors among Uyo's livestock producers and workers who handle raw meat. HIV testing, clinical eye examination and laboratory detection of anti-Toxoplasma gondii IgG antibody were all part of this descriptive cross-sectional community-based investigation. A questionnaire given by the interviewer was used to collect further information from the participants. In Uyo, the frequency of ocular toxoplasmosis (OT) and presumed ocular toxoplasmosis (POT) is 1.8% and 2.4%, respectively, among those who handle raw meat and livestock producers. Being a woman and being in the fourth or fifth decade of life are risk factors. It is recommended that toxoplasmosis awareness be raised within this professional group.Dung et al., (2022) presents the study of case-control in agricultural and behavioural factors associated with leptospirosis. The goal of the study was to pinpoint the behavioural and agricultural variables linked to leptospirosis transmission in Vietnam. From October 1, 2018, to October 31, 2019, matched retrospective hospital-community-based case-control research was carried out. The study gathered patients from eleven carefully chosen government hospitals located in three Vietnamese provinces. Meanwhile, controls were chosen from the same case communes and matched according to age (±2 years) and gender. Enzyme-Linked Immunosorbent Assay (ELISA) and Microscopic Agglutination Test (MAT) were utilized to identify confirmed cases, whereas MAT alone was utilized to identify controls with a single high

MAT titer<1:100. The case-control research has exposed the dangers associated with animal and agricultural activities as well as protective behavioural variables for human leptospirosis in Vietnam.The results recommended promoting health education and communication initiatives that focus on everyday living and agricultural methods that promote healthy behaviours. It is highly advised to use personal protection equipment (PPE) such as gowns, gloves, and boots when engaging in agricultural activities, particularly growing and animal farming.

Mlowe et al., (2023) conducted a cross-sectional study on the knowledge and awareness of Leptospirosis among households, farmers and livestock keepers. This study aims to assess the level of awareness and knowledge of leptospirosis among Unguja's peri-urban and urban populations. From January to April of 2022, cross-sectional research was carried out using semi-structured questionnaires. The primary patterns in knowledge and awareness were evaluated using descriptive analysis, and the relationships between respondents' knowledge and awareness and their demographic features were found using $\chi 2$ analysis. The aetiology of leptospirosis was unknown to the majority of respondents (64%) however a sizable percentage of respondents (68.6%) had a positive attitude towards the disease in contrast to their average knowledge, awareness, and behaviours (29.3%) and 35%). However, the farmers, fishers, livestock keepers, and medical professionals lacked information and understanding. The results also showed that, whilst educational attainment was linked to preventative measures, men had a substantial correlation with occupational physical activity. The habits of the respondents were substantially correlated with living in urban or peri-urban settings. The study's findings showed that among farmers, fisherman, livestock keepers, and healthcare professionals, there was a lack of community knowledge and awareness of the aetiology, method of transmission, and symptoms of leptospirosis. El-Shafei and Said (2023) presents a multicomponent intervention study on knowledge and behaviour among Egyptian farmers. The study's objectives were to identify potential health risks associated with sun exposure and assess the efficacy of a multicomponent sun safety intervention created especially for Egyptian farmers. From January to July 2022, 128 farmers from three villages in the Zagazig district of the Sharkia Governorate, Egypt, participated in a multicomponent interventional study. Phases one, two, and three of the study involved assessing participants' risks for skin cancer and vision screening; phase three involved conducting a multicomponent intervention that included education sessions, providing sun safety supplies and reminders, and evaluating the intervention's effectiveness after a month. Phase two involved completing a semi-structured questionnaire to assess participants' knowledge, behaviour, and exposure hazards related to sun exposure. Ultimately, the results of this study demonstrated that although while the farmers under observation were aware of the dangers of prolonged sun exposure, they generally did not practice all sun safety measures on a regular basis, particularly those that required financial assistance, such wearing sunscreen and sunglasses. This illustrates how crucial an organizational role is in shielding farmers from the sun by supplying protective gear.Choksi et al., (2023) presents the retrospective evaluation of eye irritation potential among agrochemical formulation. 192 agrochemical formulations with in vitro (OECD TG 437, 439, or 492) or in vivo (OECD Test Guideline (TG) 405) data were retrospectively evaluated in this study to see if the in vitro methods could reliably assign United Nations Globally Harmonised System for Classification and Labelling of Chemicals (GHS) eye irritation hazard classifications. Furthermore, the work evaluated the GHS Concentration Threshold (CT) approach for each of the final formulations and each of their component parts. The study's findings indicate that the GHS CT methodology and the four distinct approaches were quite predictive of formulations that wouldn't need to be classified for the risk of ocular irritation. Since the majority of agrochemical formulations fit into this category, the usage of animals for this endpoint might be greatly decreased by techniques that reliably detect mixes that are not classified.

Oddone et al., (2019) researched on peculiar sunlight exposure on agricultural workers causing Macular degeneration. Sunlight exposure at work, especially blue light (wavelength 380-550 nm), is linked to a number of diseases, including Age-related Macular Degeneration (AMD) and chronic retinal photochemical damage. This study describes a lady who worked in agriculture for 15 to 25 years while not being significantly exposed to any other occupational risk factors for AMD, and who subsequently developed this condition. Given that she was employed as a "mondina," a job that involved manually controlling weeds and relocating immature rice seedlings into fields that were flooded with water, the case is especially interesting. In addition to direct exposure to natural light, this approach involved exposure to sunlight reflection on the water's surface, a practice that was eventually superseded by the advent of pesticides. This brief case study highlights the need for more attention to be paid to preventive measures and the adoption of appropriate personal protective equipment in relation to occupational exposure to Ultraviolet-A and the short wavelength component of visible light, particularly in productive sectors where prolonged exposure to solar radiation and reflectance from surrounding surfaces is involved. Modenese and Gobba (2019) systematically reviewed macular degeneration and occupational risk factors. In affluent nations, macular degeneration which is a multifactorial disease is the primary cause of blindness in those over 50. There is currently little information available regarding potential occupational factors contributing to the disease's development. Using the MedLine and Scopus databases, the study conducted a thorough systematic search of the scientific literature on the relationship between occupational risk factors and macular degeneration. 13 peer-reviewed studies assessing occupational risk factors for macular degeneration or reporting the disease's incidence in particular worker categories were included in the review, which involved an examination of 158 articles and met inclusion criteria. The incidence of retinal degeneration in workers exposed to sun radiation was assessed in ten out of thirteen articles. Studies on occupational risk factors for macular degeneration are still rare. However, the information that is now available suggests that macular degeneration in outdoor and farm workers is linked to prolonged occupational exposure to solar radiation, particularly with regard to its blue-light component.

Febriana et al., (2023) presents a collaborative work on prevalence of pesticide related occupational diseases among Indonesian vegetable farmers. This study was conducted to determine the incidence of different occupational ailments in Indonesian local vegetable growers, such as neuropathy, nail dystrophy, and dry eyes caused by pesticide exposure. In the Ngablak District of Magelang, Central Java, questionnaires and physical examinations in the fields of dermatology, neurology, and ophthalmology were used to gather data from nearby vegetable producers. The Schirmer test and the Ocular Surface Disease Index (OSDI) questionnaire were employed. Descriptive statistics were used for analysis, and the Statistical Package for the Social Sciences (SPSS 21.0) was used. According to the study's findings, pesticides were not being stored properly and insufficient spraying equipment was discovered. Of the 105 farmers, 41.9% had skin problems related to their jobs (OSD).In 3.4% of patients, there were definitive cognitive impairments; in 28.3% of subjects, there were probable impairments. Sixty-seven percent of the individuals had neuropathies, and 28.78 percent had dry eyes syndrome. Adeniyi et al., (2023) researched on the awareness, prevalence and risk burden of cataract among adults in a rural community in Ekiti State of Nigeria. The purpose of this study is to ascertain adult cataract awareness, prevalence, and risk load in Ido/Osi LGA, a rural Ekiti State community. This study is cross-sectional and descriptive. A multi-stage sampling procedure was employed, with an estimated sample size of 361. SPSS version 25.0 was used for data analysis after ocular examinations and questionnaires were used for data gathering. The respondents' average age was 54.94±11.17. 287 respondents, or 79.5%, were well-informed about cataracts. In this study, the prevalence of cataracts is 3.9%. A considerable visual acuity cataract was detected in 49 (13.5%) of the participants. The study's conclusion noted that evidence-based policy and research, cross-sectoral cooperation, and media health education will all contribute to a decrease in the prevalence of cataracts.

Guan et al., (2023) studied on the factors that influence cataract awareness and treatment attitudes among middle-aged and older adults in rural areas. The purpose of this study was to find out how much knowledge adults 50 years of age and older in rural Qingcheng County, Gansu Province, Western China, have regarding cataracts and the factors that are related with them. From October to December 2020, 1,503 persons 50 years of age and older who were randomly selected participated in a large community-based cross-sectional survey. Both in-person interviews and eye exams were used to gather data. To find associated factors of cataract knowledge, multivariate linear regression and multivariate binary logistic regression were employed. To indicate the statistical relationships between cataract knowledge and the independent variables, the Odds Ratio (OR), coefficient (C), and 95% Confidence Interval (CI) were shown.Therefore, in order to enhance cataract surgery rates, it is advised that stakeholders in various hierarchies organize health education by taking the community's educational level into account, emphasizing surgical reimbursement ratios and awareness of cataract therapy.

Research Gap

Occluar disease has continued to gain momentum in the research community as shown in the literatures reviewed. While there are several works on this problem, there is gap in the need for ocular management system which considered data from localized communities in Benue state, to help develop model for eye disease management. The scope of this work will focus on eye disease types such as retinopathy, cataract and glaucoma respectively which are common eye disease problem affecting citizen in Benue State Nigeria.

Case Study Research Area (Benue State Nigeria)

Benue state is a region known for its rich practices in agriculture where a significant number of populations engage in farming activities. But it is unfortunate how the nature of the work exposes them to various occupational hazards such as ocular disease. Figure 1 presents the research location in Google Map of Benue, then that of Otukpo and then testbed clinic located at Lat 7.19567, Long. 8.13902.

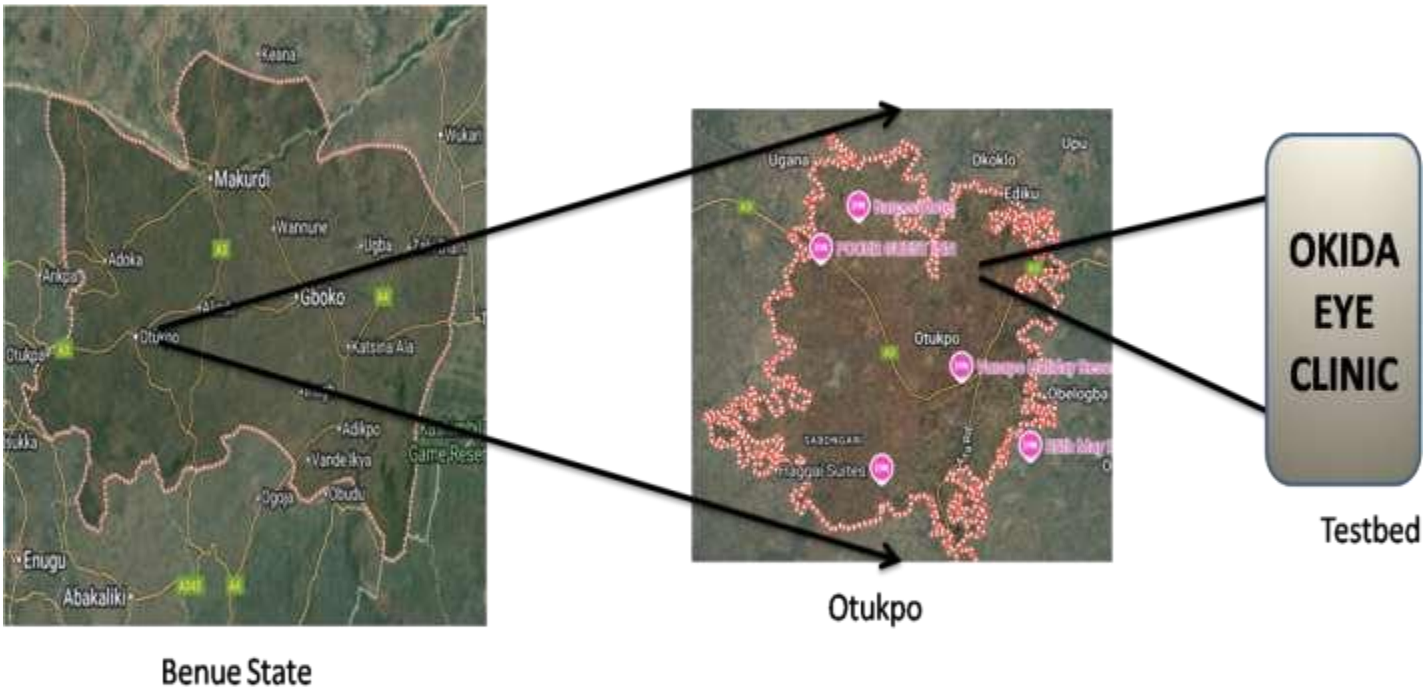

Figure 1: Google Map of the research area

In Benue, the challenge of ocular trauma worsens due to limited healthcare resources, delayed diagnosis and treatment, lack of awareness and data deficiency. These problems cause the affected population to suffer longer, have greater rates of morbidity, and have a higher chance of becoming blind. Furthermore, farmers and medical professionals are ignorant about the seriousness of ocular injuries and the value of prompt treatment. Inadequate information regarding the frequency and consequences of these injuries makes public health planning even more difficult. To solve these issues, a deep learning-based system for categorizing ocular disease associated to farmers must be developed. By improving diagnostic precision, this technology can guarantee prompt medical intervention, support healthcare professionals in environments with limited resources, and give vital support. The approach can assist avoid eyesight loss and sustain worker productivity in the agriculture industry by enhancing care accessibility and raising awareness in the neighborhood. Additionally, by gathering and analyzing data on ocular trauma incidences, public health policies and preventive measures can be improved, which will ultimately benefit Benue State's health and eye care standards.

METHODOLOGY

The methodology for the research include data collection of ocular images from selected subjects, then the data was process to ensure class balance and address issues of classification bias through data augmentation process and then applied to train a transfer learning algorithm (ALEXNET) specialized for real-time image classification to generate a model for ocular detection and classification system. The model was used to develop software for ocular disease management. Figure 2 presents the block diagram of the research method.

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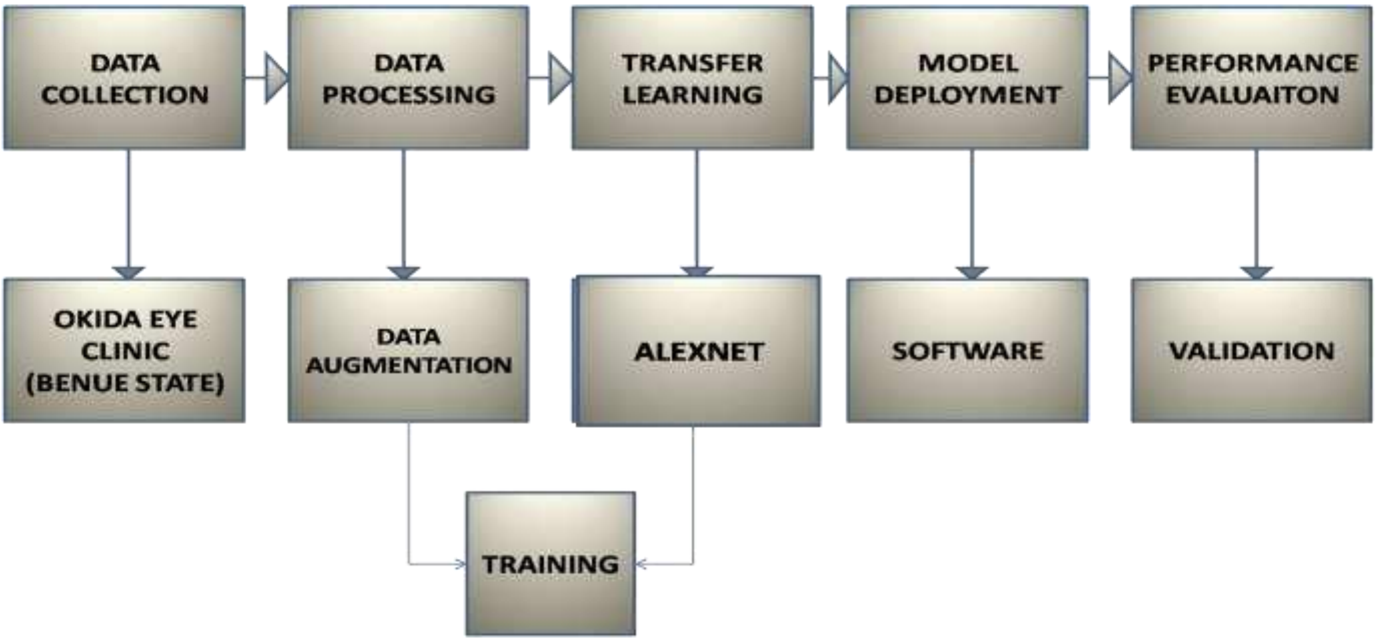

Figure 2: Block diagram of the methodology

Data collection and process analysis

The primary data for this project will be sourced from the Okida Eye Clinic located at Enugu Roundabout in Otukpo, Benue State, Nigeria. The demographic targeted encompass 47 Male (M) and 38 Female (F) farmers age between 20 and 65. A total of 2715 ocular disease images were collected, distributed across various classes of glaucoma, cataract and retinopathy. Specifically, there will be 900 images of glaucoma contributed by 55 subjects (15M and 12F), 940 samples of cataract (12M and 12F) and 875 samples of retinopathy produced from (20M and 14F). The tool for data collection is the IDRA camera, integrated with a desktop equipped with an ocular surface analyzer as depicted in Figure 3 showed served as the instrument for data acquisition.

Figure 3: Experimental testbed for data collection (Source: Okida Eye Clinic, 2025)

The collected data was analyzed using data augmentation to address class imbalances and enhance the dataset's diversity. Data augmentation involves artificially increasing the size and diversity of the dataset by applying transformations (Ebere et al., 2024). The method used is flipping, contrast adjustment, and rotation across different angles (Sochima et al., 2025). Figure 4 presents the data samples across classes while figure 5 presents the sample of data augmentation across different contrast and brightness.

Figure 4: Data sample across classes

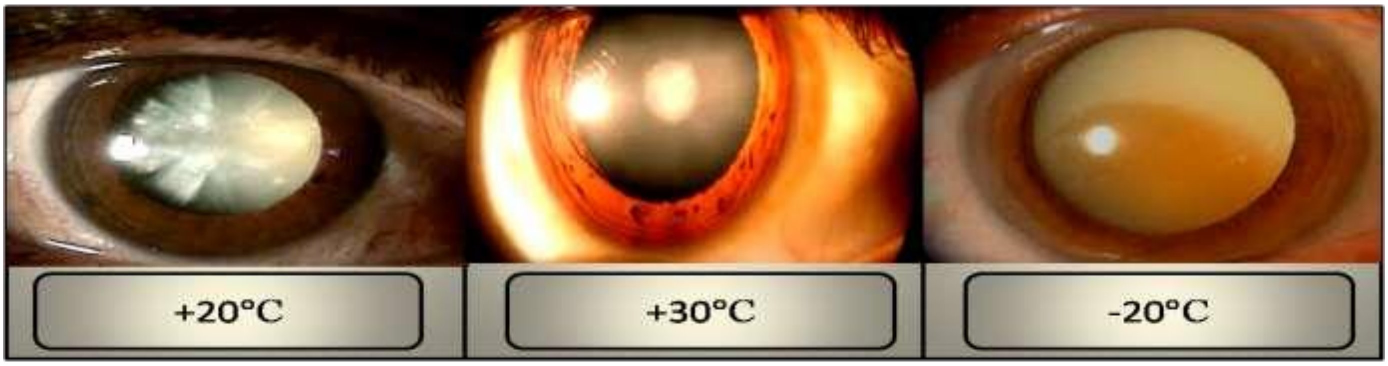

Figure 5: Data augmentation results at different contrast degree

Transfer Learning and Model development

The transfer learning model used for this work is ALEXNET. It is a pre-trained model with over one million objects containing 1000 classes. It is made of several layers which include input layer which dimension the image (227*227*3), the five convolutional layer which applied maximum pooling layer and filters for feature extraction (Kekong et al., 2019). The filter size is 3*5, 5*5 and 3*3. The fully connected layer which housed a feedforward neural network that was trained with the feature vectors to produce the model for ocular disease management.

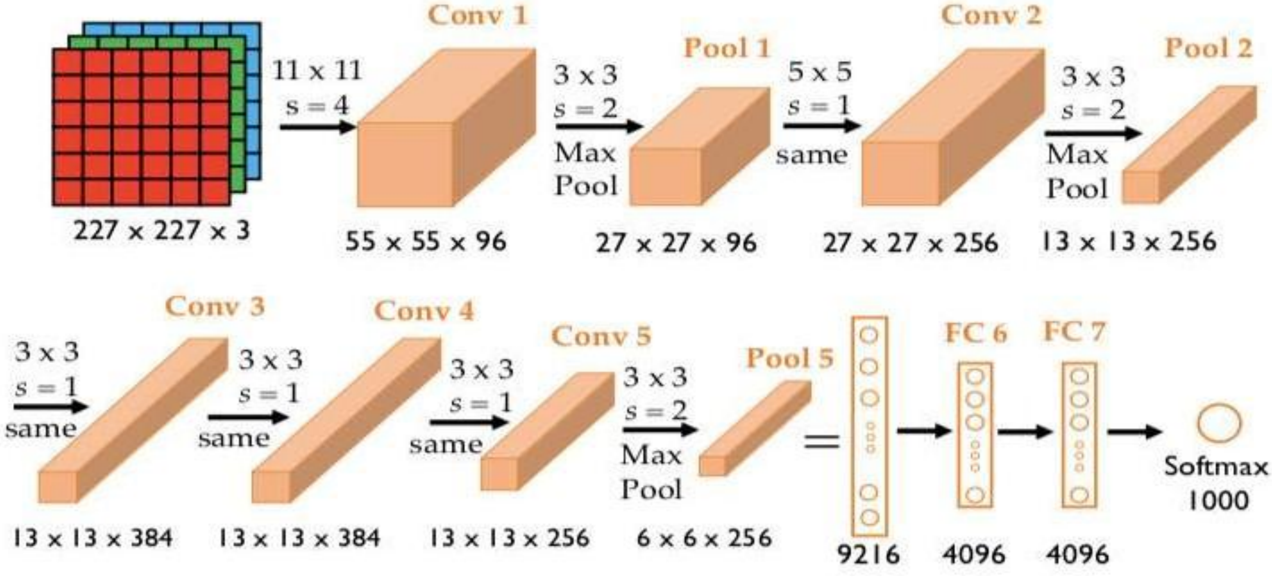

Figure 6: Architecture of AlexNet (Chidi et al., 2024)

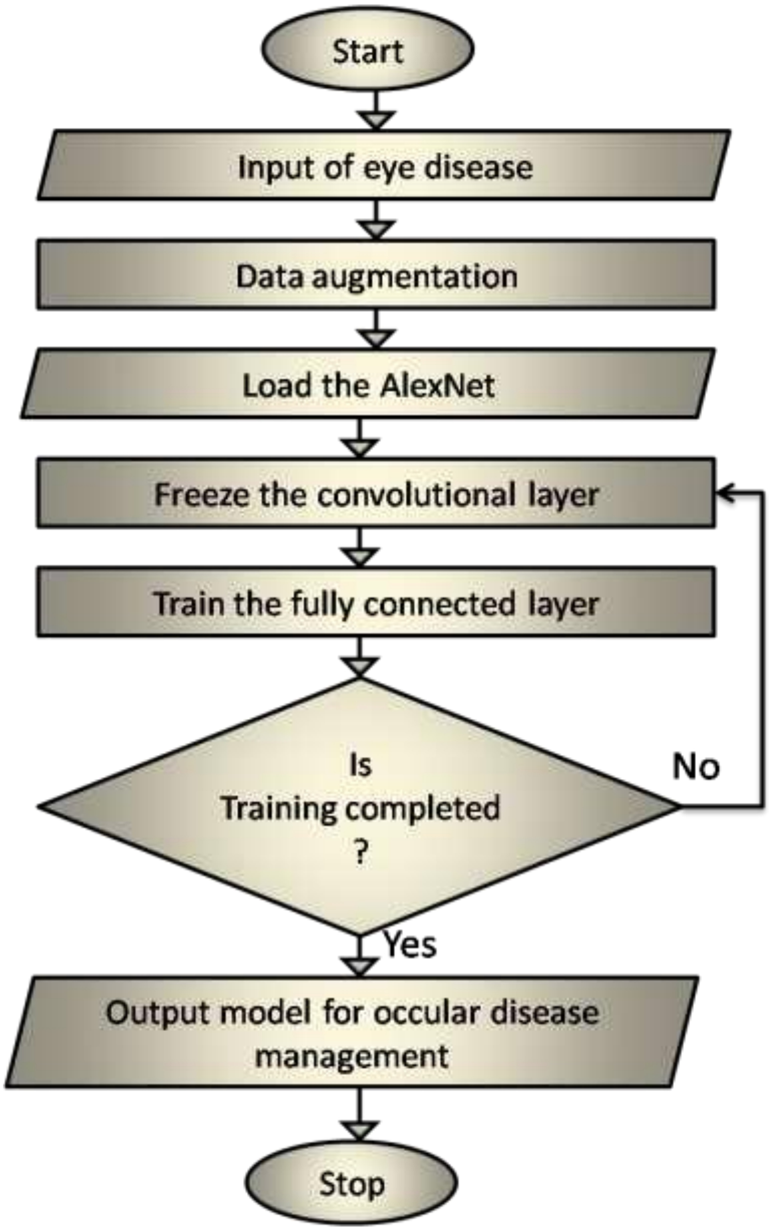

Figure 7: Flow chart of model training

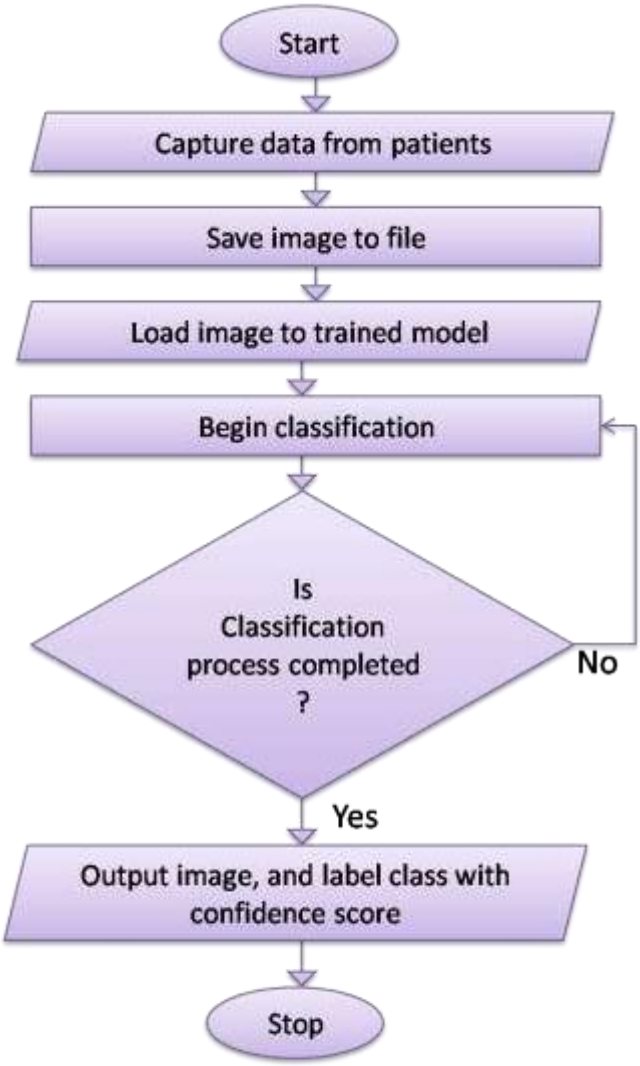

Figure 8: Flowchart of ocular model

To train the AlexNet, the data was splitted into training and validation before imported to the model, while the convolutional layers were freeze by setting the requires grad to false. Then adam optimization was applied to optimize the neurons, while accuracy in equation 1 and loss in equation 2 were applied to evaluate the performance of the model. Upon meeting stopping criteria, the model for ocular disease management was generated. Figure 7 presents the flow chart of the model training process, while figure 8 presents the flow chart of the model for ocular disease management.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad 1$$

$$\text{Cross entropy} = \sum Y_{true} * \log(Y_{predicted}) \quad 2$$

Where: TP: True Positives; TN: True Negatives; FP: False Positives; FN: False Negatives

RESULT AND DISCUSSION

This section presents the results of the model training and validation of the AlexNet model as shown in the figure

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9. The results was validated through comparison with existing models before then integrated as software for ocular disease management.

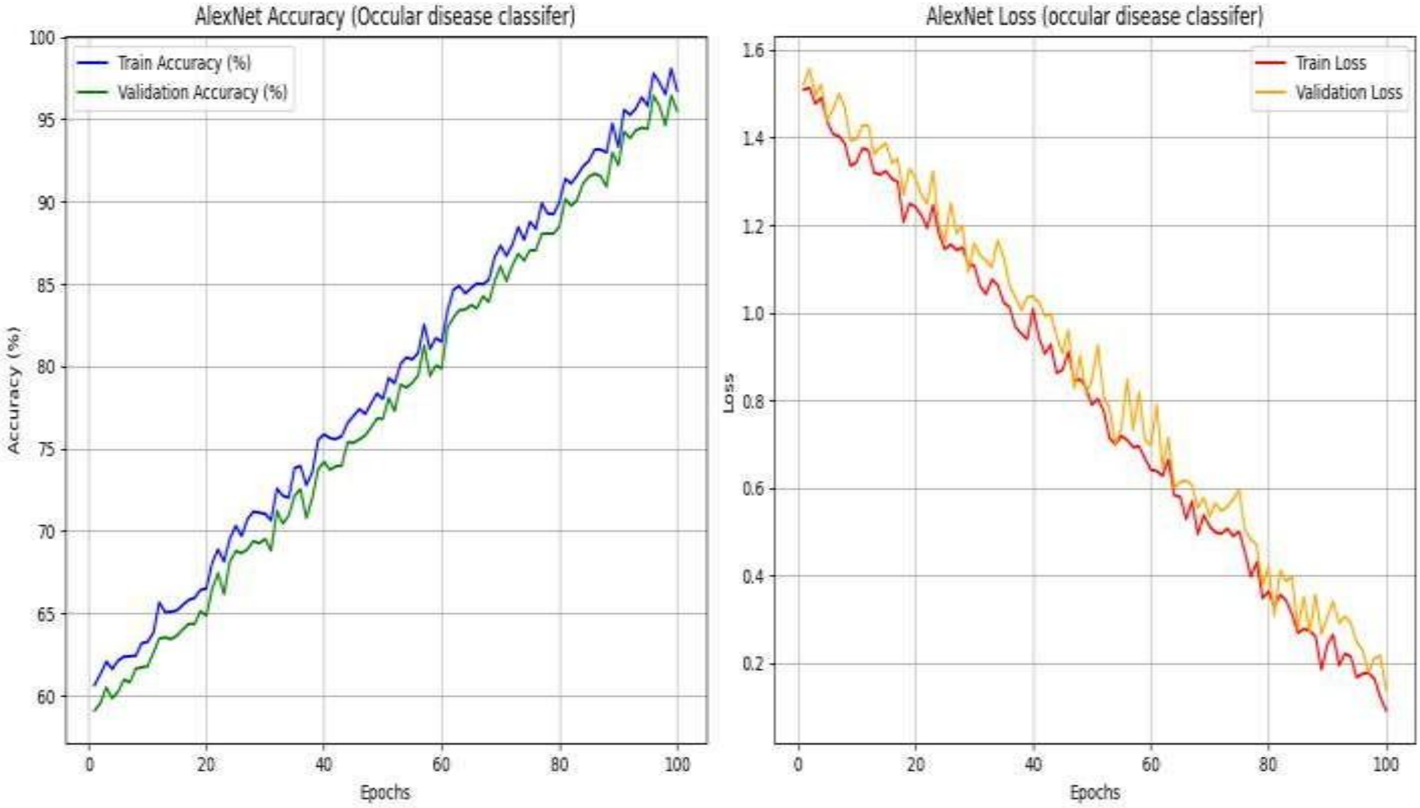


Figure 9: Result of the AlexNet training

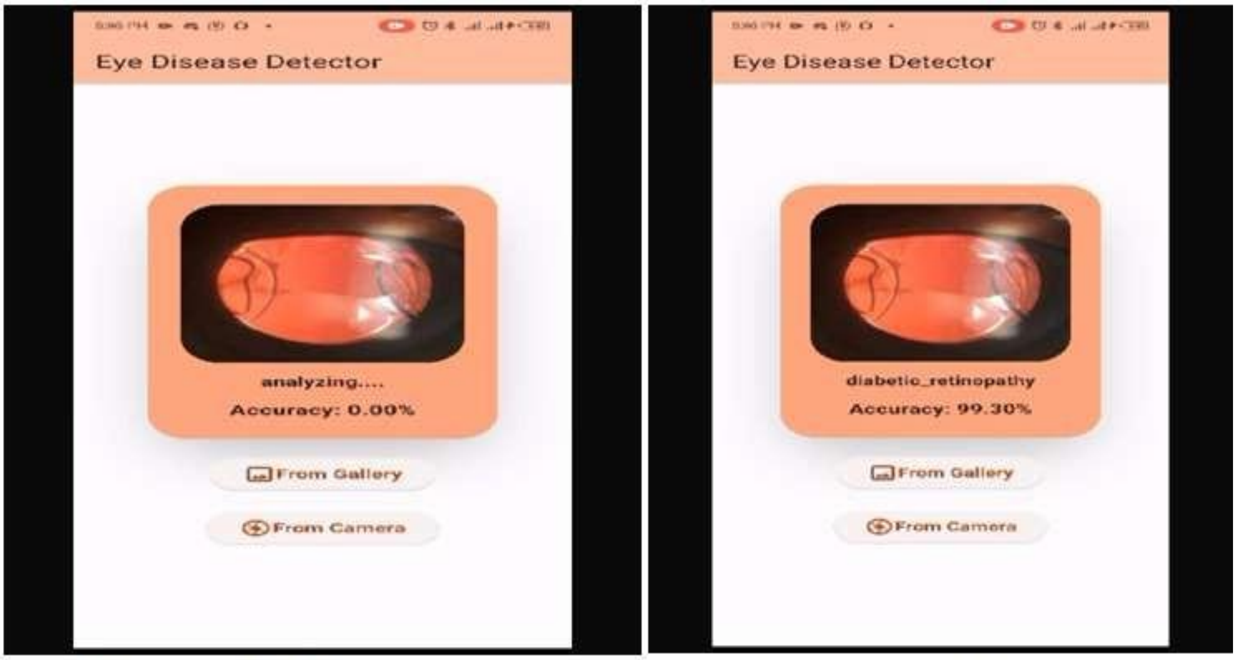
The graphs illustrate the training performance of an AlexNet model applied to ocular trauma classification over 100 epochs, showing both accuracy and loss for training and validation sets. The left plot reveals a steady and significant increase in accuracy, with training accuracy rising from approximately 61% to nearly 99% and validation accuracy closely following, ending at about 96.5%. This consistent improvement with minimal gap between training and validation accuracy indicates effective learning and strong generalization, suggesting the model is not overfitting. On the right plot, both training and validation loss decrease smoothly from around 1.5 to values below 0.2, further confirming that the model is minimizing its prediction error effectively. The parallel behavior of both curves and absence of divergence in the loss values reinforce the reliability and robustness of the training process. Overall, the plots reflect that AlexNet performs exceptionally well on this ocular disease classification task, learning progressively, generalizing accurately, and avoiding overfitting. To validate the model, we compared the results obtained with the trained AlexNet and then other state of the art algorithms. The results obtained are reported in the table 1.

Table 1: Comparative analysis

Author	**Technique**	**Results**
Araek (2025)	SVM, Random Forest, VGG16, MobileNetV1, CNN-RNN Hybrid	MobileNet: 98%, Hybrid Model: 89%; F1 Score (SVM): Glaucoma 0.97, DR 0.92
Weni et al. (2021)	CNN with 50 epochs	Accuracy: 95%
Mushtaq et al. (2020)	DenseNet-169	Accuracy: 90% (2015 data), 78% (2019 data)

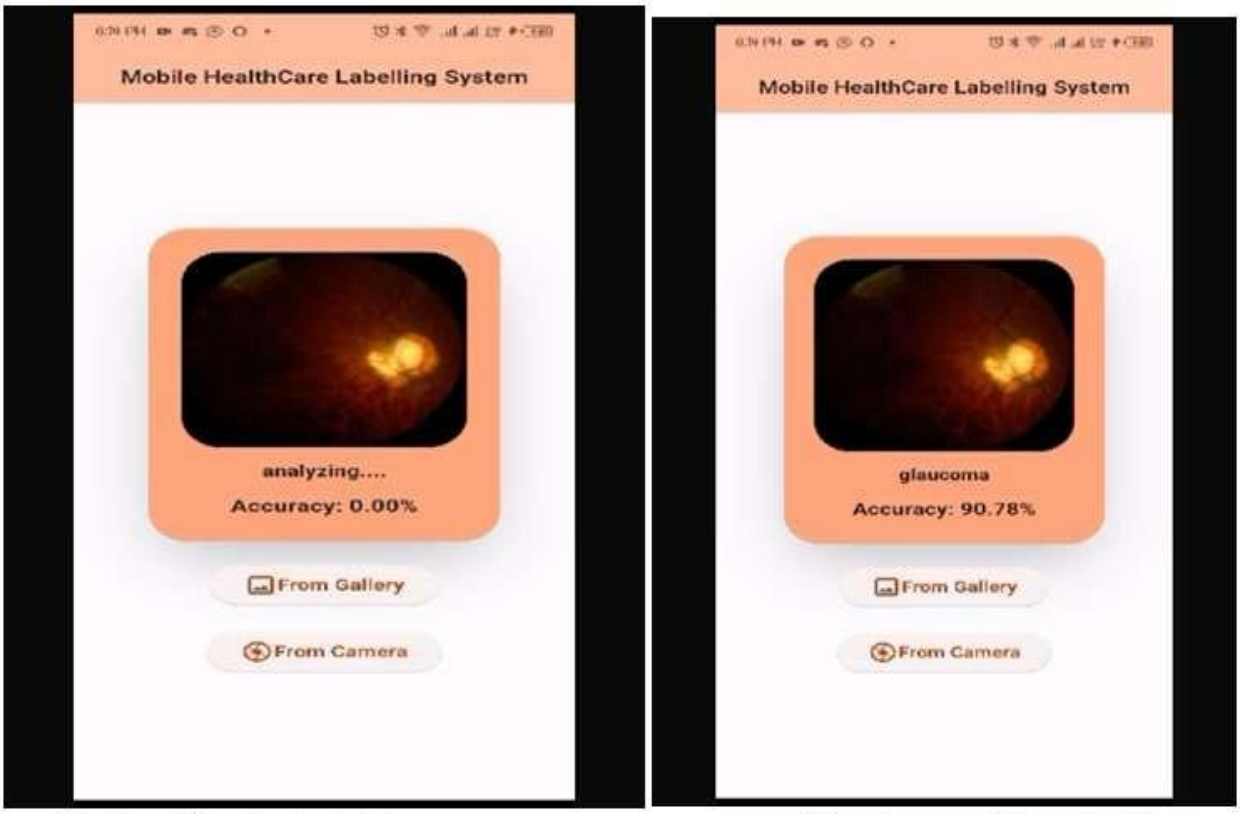
Grass-mann et al. (2018)	Automated model for AMD classification	Dataset: 126,211 images (AREDS, KORA) – No specific accuracy reported
Feng et al. (2024)	SE module + Prototype classifier + ResNet50	Accuracy: 98.75%, AUC: 0.9984, F1 Score: 0.9855
Unnamed (U-Net + ResNet34 + EfficientNetB0)	Segmentation (U-Net + ResNet34), Classification (EfficientNetB0	High AUC, F1 score, mIoU – precise accuracy not stated
Sudhan et al. (2022)	U-Net (Segmentation), DenseNet-201, DCNN	Accuracy: 98.82% (train), 96.90% (test)
Nawaz et al. (2022)	EfficientNet-B0, EfficientDet-D0	Accuracy: ORIGA 97.2%, RIM-ONE 97.96%, HRF 98.21%
Manassakorn et al. (2022)	GlauNet (CNN)	Sensitivity: 88.9%, Specificity: 89.6%, AUC: 0.89
Yi et al. (2023)	MTRA-CNN, ResNet50 with RA Block	Accuracy: 86.8%
Alkhaldi et al. (2024)	U-Net + ResNet34 (segmentation), EfficientNetB0 (classification)	Accuracy: ORIGA 100%, RIM-ONE 99%, HRF 100%; mIoU: 0.98
Mallick et al. (2023)	U-Net, SegFormer, MobileNet V2	Accuracy: 95.47%; Dice Scores: OD 0.98, OC 0.91
Prananda et al. (2023)	AlexNet, GoogleNet, InceptionV3, XceptionNet, ResNet-50,	Segmentation Accuracy: 93.61%, Classification Accuracy: 92.88%, AUC: 89.34%
Babaqi et al. (2023)	CNN, Transfer Learning with EfficientNet	Accuracy: Transfer Learning: 94%, CNN: 84%
Nazir et al. (2021)	CenterNet + DenseNet-100	Accuracy: 97.93% (APTOS), 98.10% (IDRiD)
Shukla et al. (2024)	HybridFusionNet (ViT + Attention)	Binary Classification: 99%, Multi-Class Classification: 91%
Our model	ALEXNET	Accuracy =96.5%; loss =0.2

From table 1, it was observed that while several model has been trained for classification of ocular trauma over the years, out model competes among the best wit 96.5% accuracy and also very reliable as it is trained with localized data collected from men and women in Benue state. The model was then applied for system integration as software for ocular disease management. The result of the software when tested was reported in the figure 10 and 11 considering different test sample of data collected.



(a) Classifying the test data (b) Result of classified output

Figure 10: Result when tested with retinopathy data



(a) Classifign the test data (b) outcome of the classified result

Figure 11: Result when tested with Glaucoma data

Figure 10 and figure 11 present the results of the system integration of the ocular trauma detection and classification system. The system was tested with data of glaucoma and retinopathy. Figure 10 showed the when input image of glaucoma was loaded to the software, it was able to extract feature from the image and then through the trained ocular trauma classifier was able to correctly classify the image with 99.3% accuracy. While when the software was tested with data of glaucoma, the results recorded 90.78% accuracy.

CONCLUSION

Ocular trauma has continued to threaten the well being of farmers in Benue State. The lack of low cost and reliable system for clinical examination of this problem has also contributed to the massive surge in ocular related cases within the state. To address this problem, this paper collected data of 85 subjects and then applied to train AlexNet to generate ocular detection model. The model was integrated as software for ocular management system using python programming language and then evaluated considering accuracy and loss which both recorded excellent performance. Comparative analysis was carried out to validate the work and the outcome revealed that our model competes among the best in the existing system. The software developed was tested with different ocular classes and then results recorded successful ocular trauma classification and labeling outcome.

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STATEMENT AND DECLARATION

The authors declare no conflict of interest relating to this manuscript

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