CHAPTER 1

INTRODUCTION

1.1 VISION - RELATED PROBLEMS AMONG IT EMPLOYEES

Computer vision disorder is a major cause nowadays because most people work with computers and spend hours staring at monitors. This type of eye problem is identified as computer vision syndrome (CSV), which includes discomfort in the eye and eye strain.

There are many diseases, disorders, and age-related changes that may affect the eyes and surrounding structures. As the eye ages, certain changes occur that can be attributed solely to the aging process. Most of these anatomic and physiologic processes follow a gradual decline. With aging, the quality of vision worsens due to reasons independent of diseases of the aging eye. While there are many changes of significance in the non-diseased eye, the most functionally important changes seem to be a reduction in pupil size and the loss of accommodation or focusing capability (presbyopia).

Mostly, corporate employees were affected by eye problems like eye strain, eye pain, burning sensation, double vision, blurring of vision, and frequent watering. Eyestrain is a common condition that occurs when their eyes get tired from intense use, such as while driving long distances or staring at computer screens and other digital devices. Eye Strain can be annoying. Eye pain can affect one or both eyes. They have eye pain because of things using the system. The other cause of the IT sector is that people have Dry Eyes. Computer Vision Syndrome is the name given to eye problems caused by prolonged computer use, including eye irritation (dry eyes, itchy eyes, red eyes) and dry vision, Headaches.

1.2 TYPES OF EYE DISEASE

There are many types of eye disease available but here some of them were explained in detail. They are,

1) **Glaucoma** is a group of eye conditions that damage the optic nerve. The optic nerve sends visual information from our eye to our brain and is vital for good vision. Damage to the optic nerve is often related to high pressure in our eyes. But glaucoma can happen even with normal eye pressure.

2) **Diabetic retinopathy** **Diabetic retinopathy** is a complication of diabetes caused by high blood sugar levels damaging the back of the eye (retina). It can cause blindness if left undiagnosed and untreated.

3) **Floaters**: They glide into our field of vision as tiny specks or dots. Most people become aware of them when they are outside on a sunny day or in well-lit settings. Floaters are typically normal, but they can also indicate a more serious eye condition, like a detached retina.

4) **Uveitis** This is the term used to describe a group of conditions that inflame the uvea. The majority of the blood vessels are located in the central layer of the eye. These conditions can damage ocular tissue and potentially result in the loss of an eye. It is available to all ages of people. Symptoms could disappear right away or might linger for a while. People suffering from diseases of the immune system.

5) **Nystagmus** We might have strabismus if, when we gaze at something, our eyes aren't aligned with one another. It's also known as walleye and crossed eyes.This issue won't just go away by itself. To help reinforce eye muscle weakness, our child may attend eye therapy sessions with an ophthalmologist from time to time. Typically, the surgical treatment will be performed by an ophthalmologist or eye surgeon.

6) **Conjunctivitis (Pink Eye)** This condition causes inflammation of the tissue that lines the sclera and the back of our eyelids. It might result in redness, tears, discharge, itching, burning, or the sensation that something is in your eye. All ages can purchase it. Infections, contact with irritants and chemicals, or allergies are some of the causes. Wash your hands frequently to reduce your risk of contracting it.

7) **Excess Tearing** Your feelings has nothing to do with it. Tears can be a sign of more serious medical conditions, such as. Eye infection or tear duct blockage. An eye doctor can treat or cure these problems.

1.3 RISK FACTORS OF EYE DISEASE

Risk factors for developing eye disease includes,

- **Age:** Age-related conditions including glaucoma and cataracts begin to occur more frequently. All people should undergo a thorough baseline eye exam at the age of 40, according to Safe Eyes America. Presbyopia (issues with close vision) and difficulties with glaucoma and cataracts often start to become more common around this age.

- **Diabetes:** Whether or not they have eye symptoms, all persons with diabetes should have their eyes checked once a year, and maybe more frequently if diabetes-related abnormalities are discovered.

- **High Blood Pressure (Hypertension):** The blood vessels in the retina (the back of the eye) can alter if we have hypertension. Exams of the eyes can identify and track these changes. A risk factor for the onset or progression of eye diseases such as diabetic retinopathy, glaucoma, and macular degeneration is high blood pressure.

- **Family History of Eye Disease:** Family History of Eye Disease: Our chance of acquiring an eye condition may be higher than usual if our family has a history of glaucoma, macular degeneration, early-onset cataracts, or other eye conditions. For instance, a family history of glaucoma increases a person's risk of developing the disease by 4–9 times. If we believe our eyes may be at risk, we should learn about the history of our family's eye health and get an eye test.

- **Some risks for children:** Some risks for children: Eye health risk factors for children are Symptoms or observations of a problem by family or teachers developmental or learning problems in school. diagnosed medical problems that are associated with eye disease.

1.4 SYMPTOMS OF EYE DISEASE

- Red Eyes
- Headache
- Light Sensitivity
- Lazy eye
- Burning Sensation
- Double vision
- Eye pain
- Dry Eyes
- Excess Tearing
- Blurred or Distorted vision
- Swelling

Red Eye: Blood vessels that cover their surface enlarge when they get inflamed or diseased. Your eyes appear red as a result of that. Allergies, eyestrain, late nights, little sleep, or allergies may be the cause. Consult a doctor if an injury is the root of the problem. Redeyes may be a sign of another ocular disorder, including conjunctivitis (conjunctivitis) or UV damage caused by years of not using sunglasses. Consult your doctor if non-prescription eye drops and rest do not alleviate your symptoms.

Headache: Pain in the head, neck, and face is referred to as a headache. A headache frequently signals physical or emotional problems, such as stress or high blood pressure. Depending on the source, headaches can affect different sections of the head. A headache may feel like a pounding in the temples, a sharp pain, or a dull discomfort. Some eye conditions that a headache may indicate are:

- Angle-Closure Glaucoma
- Refractive Error
- Migraine
- Photokeratitis

Light Sensitivity: The condition known as light sensitivity, sometimes known as photophobia, makes bright light uncomfortable. When outdoors or in a brilliantly illuminated environment, mild photophobia causes you to squint. When you expose your eyes to any type of light, more severe cases may cause extreme pain. Additionally, a typical sign of numerous various eye disorders, light sensitivity. Among the ailments linked to light sensitivity are:

- Cataracts
- Corneal Abrasion
- Allergies
- Keratoconus
- Migraine
- Strabismus

Lazy eye: This problem can be inherited, and it can also be brought on by a retinal degenerative disorder that is often incurable. If you have it, you must exercise particular caution in dimly lit areas. Amblyopia, often known as "lazy eye," develops when one eye is not correctly formed. That eye has poorer vision and moves more "lazily" than the other while remaining still. Infants, kids, and adults can develop it, but seldom do both eye Infants and youngsters need to get treatment right away. If It is identified and handledin the starting stage, lifelong visual issues can be prevented.

Burning Sensation: A pain kind that differs from dull, stabbing, or aching pain is a burning sensation. Neurological issues may be the cause of a burning discomfort. There are numerous additional potential causes, though. Nerve discomfort and, in some situations, nerve damage can be brought on by injuries, infections, and autoimmune diseases.

Double vision: Blinking typically manifests as double vision in both eyes. Here, issues with the eye muscles or nerves result in the eyes seeming to be slightly off-center. Although they are more prevalent in youngsters, squints do not always result in double vision.

Eye pain: Eye pain is more severe than the minor irritability you get when an eyelash or a bit of dirt gets in your eye. Eye pain goes beyond the eyestrain you would have from looking at a computer all day. When that happens, your eye will feel better when the lash or dirt is removed from it, when you can close your eyes to relax them, or when you can use a cool compress.

Dry Eyes: Your eyes may feel scratchy, gritty, and irritated due to dry eyes. Chronic dry eye is typically brought on by inadequate tear production, which prevents the eyes from remaining moisturized. However, dry eyes could also be a sign of a more serious problem. Dry eyes are a typical sign of:

- Chronic Dry Eye
- Blepharitis
- Bell’s Palsy

Excessive Tearing: There could be a number of problems if your eyes are tearing too much and are constantly moist. Tears are produced by irritated eyes in an effort to lubricate and calm them. Tearing is typically connected to:

- Bacterial Keratitis
- Blocked Tear Duct
- Conjunctivitis (Pink Eye)
- Dry Eye
- Allergies

Blurred or Distorted vision: A typical sign of many eye diseases is blurred or distorted vision. Visit your optometrist as soon as you can if you experience any sudden, noticeable changes in your eyesight. The following common eye problems can result in hazy or distorted vision**:**

- Age-Related Macular Degeneration
- Astigmatism
- Cataracts
- Conjunctivitis (Pink Eye)
- Detached or Torn Retina
- Keratoconus
- Macular Edema
- Refractive Error

Swelling: Trauma to the head, neck, or face may result in swelling on or around the eye. It is possible for the tissues of the eye or eyelids to irritate and swell, giving them the typical puffy, discolored appearance. Swelling could be a sign of a significant eye issue. Typical problems include:

- Black Eye
- Blepharitis
- Blocked Tear Duct
- Cellulitis
- Conjunctivitis (Pink Eye)
- Corneal Ulcer
- Scleritis
- Graves' Disease

When to see a doctor

seek emergency medical care if you have these eye disease symptoms

- Eye Strain
- Eye pain
- Burning Sensation
- Headache
- Frequent Watering

Eye disease is easier to treat when detected early, so talk to our doctor about our concerns regarding our eye problems. If we're concerned about developing eye disease, talk to our doctor about steps we can take to reduce our eye disease risk. This is especially important if we have a family history.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter, three algorithms were used to guide the use of various methodologies and techniques. All methods and techniques employed are distinct from one another. Each referenced paper is discussed here with its implementation algorithms.

2.2 LITERATURE REVIEW

Ipsita Sutradhar et.al.,[1]"Eye diseases: the neglected health condition among the slum population of Dhaka, Bangladesh." Eye problems are among the leading causes of nonfatal debilitating ailments worldwide. In Bangladesh, 21.6% of adults have impaired eyesight, while 1.5% of individuals are blind. Therefore, the purpose of this study was to determine the community-based prevalence of eye disorders and related risk factors among Dhaka city's slum residents. Two stages of the investigation were completed. In the first stage, 1320 homes in three specifically chosen slums in Dhaka city were the subject of a survey employing multistage cluster sampling. One family member (age 18) from each household was chosen at random to be interviewed by trained data collectors using a standard questionnaire. Following that, each participant was asked to participate in the study's second phase. Following the request, 432 of the 1320 participants entered the tertiary care facilities, where an ophthalmologist clinically evaluated them for the presence of eye problems. Stata 13 was used to carry out a number of descriptive and inferential statistics. Of the 432 study participants in all, 68.6% were women, 82.6% were married, and 98.8% were Muslims. Nearly all (92.8%) of them had a clinical diagnosis of an eye illness. Refractive error (63.2%), conjunctivitis (17.1%), vision impairment (16.4%), and cataract (7.2%) were the most common eye illnesses. It was discovered that refractive error was highly correlated with advanced age, female gender, and an income-producing occupation. Although there was a negative correlation between cataract and education level, there was a positive correlation between cataract and visual impairment.

Mohammad Muhit et.al.,[2]"Epidemiology of eye diseases among children with disability in rural Bangladesh: a population-based cohort study." To describe the epidemiology of ocular disorders in Bangladeshi rural children with disabilities. Using the key informant technique, we created a population-based cohort of kids with disabilities. Children with disabilities (such as physical, visual, auditory, speech, or epilepsy) under the age of 18 were included. We employed thorough ophthalmological evaluations performed by a multidisciplinary team composed of an ophthalmologist, an optometrist, a doctor, and a physiotherapist in accordance with World Health Organization (WHO) regulations. The following WHO criteria were used to describe vision impairment, blindness, and severe visual impairment (SVI). 1274 children aged 6 to 17 were evaluated between October 2017 and February 2018 (interquartile range: 6 to 13 years, 43.6% female). 5.6% (n = 71) had a visual impairment, while 6.5% (n = 83) were blind or had SVI. 47% (n = 39) of the individuals in the group with blindness or SVI had cortical blindness, and of those, 79.5% (n = 31) had cerebral palsy (CP).

Kadir SMU et.al.,[3]" Prevalence of Refractive Errors among Primary School Children in the Southern Region of Bangladesh." Refractive errors are thought to be preventable disorders that might cause vision impairments in young children. In order to evaluate the refractive errors among primary (elementary) school students, a cross-sectional study was carried out between January and May of 2021 in a tertiary-level specialized eye facility in the southern part of Bangladesh. All of the elementary school students using the hospital's outpatient department comprised our study population. In the study, we did, however, employ practical sampling. 252 primary school-aged children were investigated in total, 148 (58.7%) of whom were males and 104 (41.3%) of whom were girls. The youngest of them was seven years old, and the oldest was twelve. The kids were 9.67 years old on average. Myopia, which affected 103 children, or 50% of them, was the most common refractive error, followed by astigmatism (77 children, or 37.4%), and hyperopia (26 children, or 12.6%). Myopic astigmatism made up 58 (75.3%) of all cases of astigmatism, whereas mixed astigmatism was detected in 13 (17%) youngsters and hyperopic astigmatism in 6 (7.8%). 17 children (6.7%) were found to have amblyopia. After the refractive problems were corrected, the visual acuity improved.

Rubina Sarki et.al.,[4]”Image Preprocessing in Classification and Identification of Diabetic Eye Diseases.” The group of eye issues known as diabetic eye disease (DED) affects diabetic patients. Finding DED in retinal fundus imaging is important because early diagnosis and therapy can eventually reduce the risk of vision loss. Early DED classification and identification heavily rely on the retinal fundus picture. The amount and quality of images used to build an appropriate diagnostic model from a retinal fundus image are highly dependent. The significance of image processing for DED classification is the subject of a rigorous investigation in this research. Several stages were taken to complete the suggested automatic classification framework for DED: improving the picture quality, segmenting the image (using a region of interest), enhancing the image (using a geometric transformation), and classifying the result. Traditional image processing techniques combined with a newly developed convolutional neural network (CNN) architecture produced the best results. The classic image processing method in combination with the newly developed CNN provided the best performance and accuracy for DED classification issues. The experiment's findings demonstrated sufficient accuracy, specificity, and sensitivity. All of these algorithms provided effective results.

Mr. Langade Umesh et.al.,[5]”Review of Image Processing and Machine Learning Techniques for Eye Disease Detection and Classification.”Clinical practices like diagnosis, treatment, and monitoring face new hurdles as a result of the ever-growing amounts of patient data being collected in the form of medical images. Image mining is the process of looking through data to find important insights. It is used in machine learning and image processing. Using image processing to detect diseases in medical photographs is important. The identification and categorization of diseases are based on the type of human organ and its picture. It is possible to automate and/or support doctors with clinical diagnosis using image processing and machine learning techniques. The implementation of various image processing and machine learning approaches for the identification of eye illnesses is discussed in this research. In this research, we explore various image processing and machine learning algorithms for the identification and categorization of eye diseases. In this study, we discuss machine learning methods like NB, KNN, SVM, AUC, HMM, and others, in addition to image processing methods like noise reduction, sharpening, contrast enhancement, and image segmentation. The study defined a review of medical image processing and machine learning algorithms for identifying and categorizing photos of eye diseases. All of the image processing methods and algorithms presented in the paper will be used in the proposed system. With the use of image processing and data mining techniques, the suggested system can detect and recognize eye diseases.

Masahiro Oda et.al.,[6] "Automated eye disease classification method from anterior eye image using anatomical structure focused image classification technique." An automated technique for classifying infectious and non-infectious disorders from anterior eye pictures is presented in this work. In cases of infectious and non-infectious diseases, different treatments are used. Differentiating them from a treatment plan must be determined using the anterior eye pictures. Empirically, ophthalmologists can tell them apart. It is required to classify them quantitatively using computer aid. We provide a method for automatically categorizing anterior eye pictures into cases of infectious or non-infectious disease. photos of the front eyes have substantial fluctuations in illumination brightness and eye location. This makes classification challenging. If we concentrate on the cornea, the locations of the opacified patches change between cases of infectious and non-infectious disorders. As a result, we use an object detection strategy that focuses on the cornea to complete the anterior eye image classification challenge. The term "anatomical structure focused image classification" might be used to describe this method. To distinguish between corneas with infectious diseases and corneas without infectious diseases, we apply the YOLOv3 object detection approach. The classification of an image is determined using the detection result. 88.3% of the photos in our studies employing anterior eye images were accurately identified using the suggested strategy. substantial fluctuations in illumination brightness and eye location.

Fourcade Arthur et.al.,[7] “Deep learning in medical image analysis: a third eye for doctors “ Medical artificial intelligence (AI) is a rapidly expanding topic. Convolutional neural networks (CNNs), one of the most popular deep learning algorithms today, provide up enthralling possibilities for automating medical picture processing. We searched the existing research to answer the question, "Can deep learning algorithms for image recognition improve visual diagnosis in medicine?" in this systematic review study. substantial fluctuations in illumination brightness and eye location. We offer a thorough study of studies utilizing CNNs for medical image analysis that were released in the literature before May 2019. The following criteria were used to filter articles: the approach to image analysis (detection or classification), the architecture of the algorithm, the dataset used, the training phase, the test, the comparison method (with experts or others), the results (accuracy, sensibility, and specificity), and the conclusion. We found 352 publications in the PubMed database, but we eliminated 327 of them because they were review articles or because they involved tasks other than segmentation or detection that were evaluated. The 25 papers featured covered a wide range of medical professions and were written between 2013 and 2019. Most of the authors were from North America and Asia. The CNNs needed a lot of high-quality medical images to train, which frequently required international cooperation. The most popular CNNs, including AlexNet and GoogleNet, were demonstrated to be applicable to medical images. These CNNs were created for the analysis of natural images. CNNs won't take the position of medicalprofessionals, but they will help streamline regular activities, perhaps improving our practice. Radiology and pathology are two fields that will see significant transformations. The creation and use of such devices require the involvement of medical professionals, particularly surgeons.

U Rajendra Acharya et.al.,[8]“Computer-based classification of eye diseases “ Elderly eye diseases are a serious health issue. Age-related declines in eye tissue function and an increase in ocular disease are two effects of aging. Cataracts, iridocyclitis, and corneal haze are the most frequent causes of age-related eye disorders and vision impairment in seniors. Iridocyclitis, an inflammation of the iris (the colored area of the eye), and corneal haze, a side effect of refractive surgery marked by cloudiness of the normally clear cornea, are twodifferent conditions. An intelligent computer-based classification method for these eye disorders is very helpful for disease management and disease diagnosis. This study compares three categorization methods for four different types of ocular data sets (three different kinds of eye diseases and a normal class). Three different types of classifiers are used in our protocol: artificial neural networks, fuzzy classifiers, and neuro-fuzzy classifiers. These raw photos are used to extract features, which are then input into these classifiers. A database of 135 people is used to run these classifiers using the cross-validation method. We show that these classifiers have a sensitivity of over 85% and a specificity of 100%, and the results are quite encouraging.

Jyostna Devi Bodapati et.al.,[9]”Deep convolution feature aggregation: an application to diabetic retinopathy severity level prediction” One of the leading causes of vision loss and blindness in people throughout the world is diabetic retinopathy (DR). Patients with long-term diabetes are more likely to have DR. By detecting the disease in its earliest stages, theautomation of DR diagnosis prevents many individuals from going blind. In this study, we use characteristics taken from previously trained models to characterize DR images and offer a robust model for DR severity level prediction. Utilizing pooling and fusion techniques, the activation filter values from various VGG-16 convolution blocks are recovered and aggregated. By reducing noisy and redundant features using pooling and fusion techniques, the aggregation module creates a compact, informative, and discriminative representation of the retinal pictures. To determine the degree of DR severity, these feature representations are loaded into the suggested DNN architecture. Our suggested strategy achieves a new state-of-the-art performance on the benchmark Kaggle APTOS 2019 contest dataset with an accuracy of 84.31% and an AUC of 97. Experimentaltests show that the suggested model performs better than the current models, especially when it comes to severe and proliferating DR pictures.

Md. Sajjad Mahmud Khan et.al.,[10] "Cataract Detection Using Convolutional Neural Network with VGG-19 Model" One of the most common causes of vision loss and blindness in the globe is cataract. Approximately 50% of people worldwide are blind. Thus, early cataract detection and prevention may lessen visual impairment and blindness. Contrary to cataract, the development of artificial intelligence (AI) in the field of ophthalmology is extremely fruitful for ailments including glaucoma, macular degeneration, diabetic retinopathy, corneal problems, and age-related eye diseases. In contrast to conventional pre-trained Convolutional Neural Network models, a unique deep neural network called CataractNet is proposed for automatic cataract identification in fundus images with an average accuracy of 99.13%. The computational cost and average running time are also greatly reduced. TLDR This model successfully predicted cataract illness on the dataset with a training loss of 1.09%, a training accuracy of 99.54%, a validation loss of 6.22%, and a validation accuracy of 98.17%.

Rubina Sarki et.al.,[11]"Convolutional Neural Network for Multi-class Classification of Diabetic Eye Disease" Early diagnosis and treatment of Diabetic Eye Disease (DED) improves prognosis and lowers the risk of visual loss that is permanent. The screening of retinal fundus pictures is a vital procedure commonly employed for the first diagnosis of individuals with DED or other eye problems. However, manual detection with these photos is time-consuming and labor-intensive. Researchers have tried to apply deep learning (DL) technology to diagnose retinal eye illnesses from retinal fundus photographs because DL has recently been shown to bring impressive benefits to clinical practice. While the classification of multi-class retinal eye illnesses remains an unsolved task, DL techniques in machine learning (ML) have attained state-of-the-art performance in the binary categorization of healthy and sick retinal fundus pictures. Consequently, multi-class DED is taken into account in this study's attempt to create an automated classification framework for DED. Multiple DED detection from retinal fundus pictures is a significant research area with applications. The numerous retinal fundus photos from the publicly accessible dataset that had been annotated by an ophthalmologist were used to evaluate oursuggested model. A brand-new convolutional neural network (CNN) model was used in this experiment. Using our suggested model, we were able to classify objects into multiple categories with a maximum accuracy of 81.33%, 100% sensitivity, and 100% specificity.

SUMMARY

We have referred to 13 papers regarding the eye disease prediction, in which most authors focused on eye-related common diseases and IT employees affected by stress, neckpain, etc. No one wants to talk about how IT employees are affected by eye diseases. So we are taking an eye disease prediction survey among corporate employees using machine learning techniques.

CHAPTER 3

PROPOSED WORK

3.1 MACHINE LEARNING CLASSIFERS

In the proposed approach machine learning algorithm has used for fake news detection. Machine learning algorithms are being used all over the place. The majority of ML algorithms are based on mathematical operations. When the input dataset includes numerical values, implementing an algorithm is a simple operation. However, if the dataset includes categorical data, certain transformations must be performed before implementing machine learning algorithms. Since the dataset for detecting fake news includes text, additional processing is required. Textual datasets can be handled with Natural Language Processing techniques provided by ML. Good results can be obtained by analysing the main properties of a dataset with the model that is best suited for that problem. Machine learning algorithm has been used for identifying the fake news. Five classifications have been used for identifying of fake news. Those algorithms are Naïve Byes, Decision Tree classification, Logistic Regression, Random Forest classification, SVM algorithms. The Data set has been opted from kaggle. It has a total of 23,481 fake news articles and 21,417 true news articles.

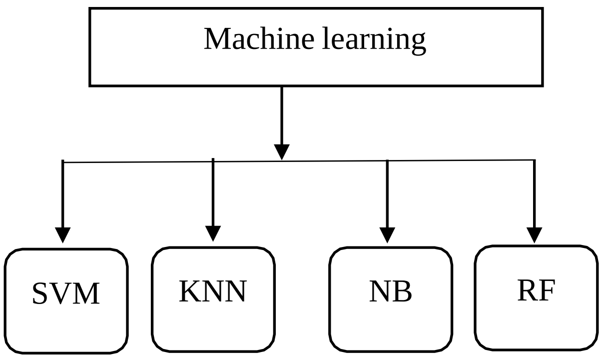

Figure. 3.1 Machine learning classifications

3.2 WORKFLOW DESCRIPTION

3.2.1 Dataset Collection

We approach some doctors and get the relevant information regarding eye pain for the attributes. They claim that if someone continuously keeps on watching the system they'll most probably get affected. With this information, we have framed a questionnaire for the dataset which is in an unstructured format.

3.2.2 Data Pre-processing

In this stage, the given datasets were pre-processed to remove the noise such as mail-Id etc. Pre-processing was done using the NLTK toolkit which is an open-source and broadly used NLP library. It has built-in functions and algorithms such as nltk.

3.2.3 Dataset

In the prediction of eye disease in corporate companies we used real time dataset.

3.2.4 Naive Bayes

Naïve Bayes algorithm is a supervised learning algorithm, which is based on Bayes theorem and used for solving classification problems. It is mainly used in text classification that includes a high-dimensional training dataset. Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions. It is a probabilistic classifier, which means it predicts on the basis of the probability of an object.

Algorithm:

STEP 1: Predict the frequency tables from the given dataset.

STEP 2: To fit the naïve bayes model to the training dataset.

STEP 3: To generate likelihood table by finding the probabilities of given features.

STEP 4: Use the bayes theorem to calculate posterior probability.

STEP 5: Create the confusion matrix to check accuracy of naïve bayes classifier.

STEP 6: Test the accuracy of the result using confusion matrix.

STEP 7: Visualize the training dataset result using naïve bayes classifier.

3.2.5 SVM

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

Algorithm:

STEP 1: Select the two features $X_1 + X_2$.

STEP 2: Classify the pair (X_1, X_2) of given coordinates.

STEP 3: Select the best boundary or region called hyperplane to find the best line or decision boundary.

STEP 4: The closest points of the lines in found from both the classes, called as support vectors.

STEP 5: The distance between vectors and hyperplane is measured and formed as margin.

STEP 6: To maximize the found margin to predict effective distance.

STEP 7: The optimal hyperplane with maximum accuracy along with extended margin is found.

3.2.6 KNN

One of the important fundamental Machine Learning tasks is the K-NN. K-NN is basedon the technique of Supervised Learning. The K-NN method takes that the new data and previous cases are similar and places the new case in the most similar category to the existingcategories.

The K-NN algorithm saves all possible data and assorts fresh data points according to their similarity. That is, as fresh data appears, the K-NN algorithm can quickly classify it into a useful package type. If the training data is large, it may be more effective.

Algorithm:

STEP 1: Select the number K of the neighbours.

STEP 2: Calculate the Euclidean distance of **K number of neighbours.**

STEP 3: Take the K- nearest neighbours as per the calculated Euclidean distance.

STEP 4: Among these K -neighbours, count the number of the data points in each category.

STEP 5: Assign the new data points to that category for which the number of the neighbour is maximum.

STEP 6: Our model is ready.

3.3 FEATURE EXTRACTION

Feature extraction is a dimensionality reduction procedure that reduces an initial collection of raw data to more manageable groups for processing. The enormous number of variables in these large data sets necessitates a large number of computational resources to process. Feature extraction refers to approaches that choose and/or combine variables to form features, hence minimizing the quantity of data that must be processed while properly and thoroughly describing the original data set.

3.4 TRAINING THE CLASSIFIER

Finally, using the kfold technique, the datasets were separated into training and testing sets once all of the preceding processes were completed. The random search hyper-parameter tuning approach is used to select the best hyper-parameters. Hyper-parameters are machine learning models' default values that have a direct impact on their performance during the training process. Each model comes with default parameter values, however this does not ensure optimal performance. Furthermore, determining the ideal value of hyper-parameters prior to training is unlikely. As a result, many combinations were evaluated.

3.5 RESULTANT CLASSIFICATION

By implementing all the above steps further, we move to the classification of the result whether the obtained result. On the basis of various ML techniques, we conclude the output of the generated result. Target denotes 0 as well as denotes 1. Finally, we determine how much accuracy attend by the implemented ML algorithm.

Here first of all collection of the relevant dataset is required, following that step data pre-processing and cleaning are going to be done using various methodology like

Tokenizing, steaming, Stop word removal, etc. Then further move to the next step and feature extraction will be done. Once the feature extraction is done in the next stage dataset is going to be trained and tested. After implementation of all previous steps at the last result classification will happen if the result got as 0 which means it is target similarly if the result got as 1 that shows that it is true. For all the above steps and procedure different machine learning techniques is used. Every machine learning technique will give a different result and I will compare the entire machine learning algorithm and move forward with the K nearest neighbour as the best accuracy obtained.

SUMMARY

In this proposed work, three machine learning algorithms which are Naive Bayes, Support Vector Machine, and KNN are used to identify the eye disease. Based on the accuracy attended by all the algorithm it is obtained that K nearest neighbour performs well among all and get the highest accuracy of 89.25%.

CHAPTER 4

PROJECT IMPLEMENTATION

4.1 IMPLEMENTATION STEP

In this work, Python is used to perform all of the experiments. Python is the most commonly used machine learning method. The selection of a dataset is important since the entire process is based on the fields and records. The dataset for the eye disease prediction is get from the real time data set. It has a total of 200 people's data and 58.2 % of people with a eye problem. The rest of the people without have an eye problem. The dataset has beensplit into two categories firstly a training set and secondary testing set. While splitting a training set and test set, a training set is marked by 80% of whole data set whereas of datasethas marked by test set.

There are two datasets has taken for proposed work, in *Figure 4.1* Y axis represents total number of count available in each dataset and X axis denotes a list of the dataset used in proposed work.

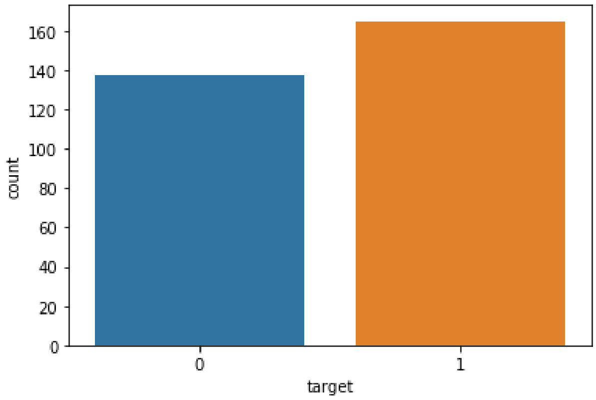

Figure. 4.1 Percentage of patience with eye problem

The data is now ready to be analysed. Four classifications have been applied those algorithms are Naïve Bayes, SVM, and KNN. After applied that algorithm, in *figure.4.2* the bar graph shows the analysing the sex feature and in *figure.4.3* the bar graph shows that the Analysing the 'Eye Pain Type' feature.

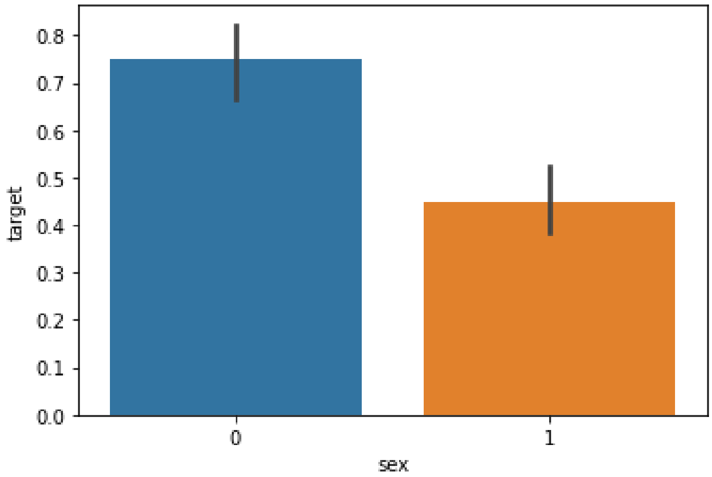

Figure. 4.2 Analysing sex feature

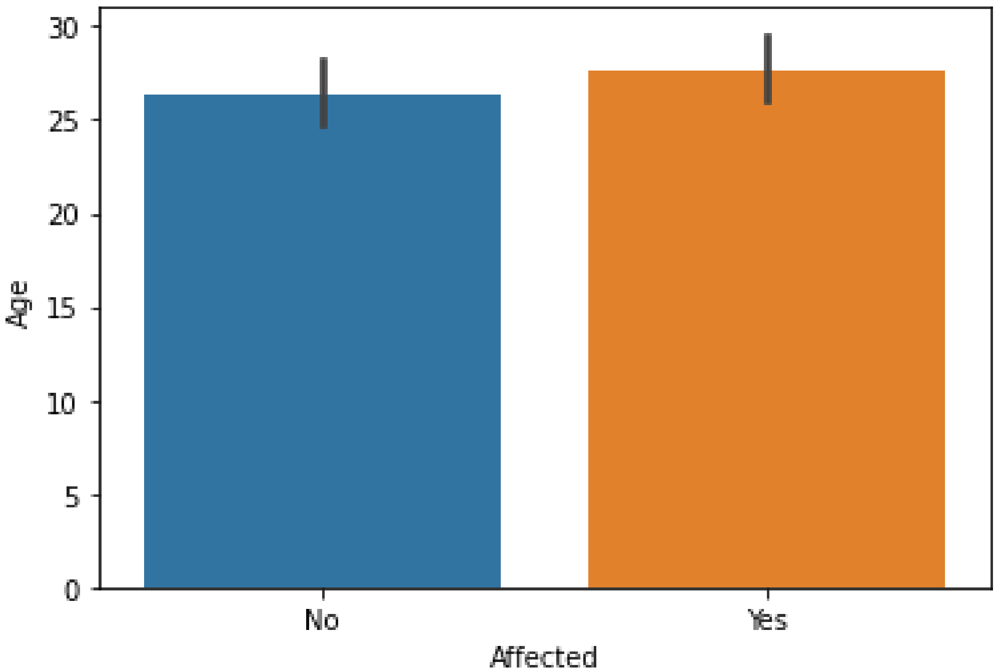

Figure.4.3 Analysing **the 'Eye Pain Type' feature**

4.2 PROCEDURE DESCRIPTION

- Data pre-processing - The transformations applied to data before it is fed into the algorithm are referred to as data pre-processing. The method of transforming raw data into a clean data set is known as "data pre-processing." In other words, data collected from different sources is received in raw format, making analysis impossible. When using a model in Machine Learning projects, the data must be formatted correctly in order to get better results. Among the implemented Machine Learning algorithms, the best-suited Machine Learning algorithm is found and measured.

- Classification - When the output has finite and discrete values, classification is the most efficient method of supervised learning since it defines which class data elements belong to. Furthermore, it assigns a class to an input variable. The supervised learning community includes classification. The goals were also shown the input data. Credit recognition, medical diagnosis, and target marketing are only a few of the applications for classification. The targets were also shown the input data.

- Performance Evaluation - Every data science project requires evaluating the output of a machine learning model. The aim of machine learning model evaluation is to figure out how well a model generalizes to a given dataset.

SUMMARY

There are various procedures are followed for the implementation of the project for attending most accurate result. While using Machine Learning algorithms, the proposed work is focused on the terms like Dataset collection followed by Data pre-processing and data cleaning. Once data pre-processing done Feature Extraction and training the classification work will be done. After implementation of all above steps the system predict actual classification either it is fake or true news

CHAPTER 5
RESULTS AND DISCUSSION

In this work, the dataset is collected from the real time data, and applied in the Python. It is one of the popular programming languages and the language is used in this work to detect the fake news. In this work, machine learning algorithms such as Naïve Bayes and SVM are used. The evaluated results are compared on basis of correctly classified instances, incorrectly classified instances, accuracy, True Positive Rate and False Positive Rate.

In this work, after applying of eight different Machine learning algorithms whichis KNN, Naïve Bayes, SVM. A comparison chart is prepared for comparing Machine learning algorithms after all classification algorithms have been implemented.

So, in this work, the KNN gave better accuracy of 89.25% as compared to other algorithms to predict eye disease. Which shows KNN has better accuracy level. Dataset has been same for each classifier but when it came about result KNN shows the very high accuracy in compare of all others.

The accuracy score achieved using K-Nearest Neighbour's is: 89.25%
The accuracy score achieved using Support Vector Machine is: 70.13%
The accuracy score achieved using Naive Bayes is: 51.92 %

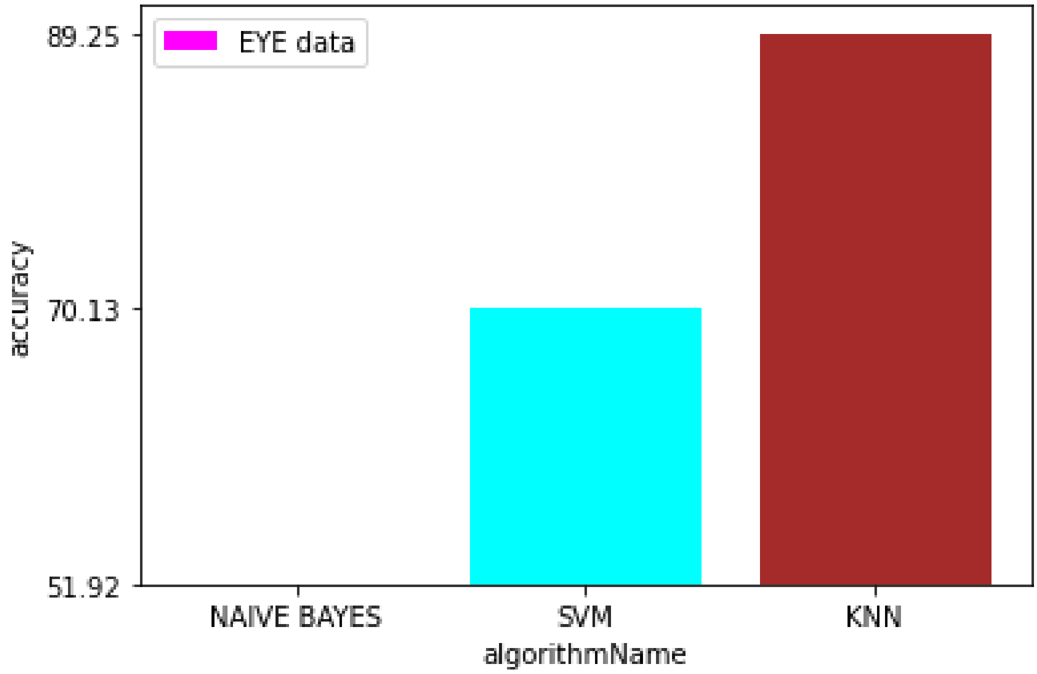

Figure. 5.1 Accuracy of classifier

In the **figure 5.1** X axis represents the different algorithms used in the proposed work, Y axis represents the accuracy attend by each algorithm. K-Nearest Neighbour having 89.25% which is standing 1st in accuracy level in spite of all the three and the Naïve Bayes has the less 51.92% accuracy of as compared Support Vector Machine. Deflection of Accuracy is very minor but it deflected in points which is easily showable here in the above diagram. Looking upon the Naive Bayes their accuracy level is 51.92% whereas Support Vector Machine accuracy level has 70.13%.

CHAPTER 6

CONCLUSION AND FUTURE WORK

In this work, there are three types of machine learning algorithms used. Naive Bayes, SVM, and K-NN classification techniques are examples of these algorithms. These are the algorithms that produce the best results when used to create a tool for detecting eye disease. SVM and Naive Bayes have the lowest accuracy in spite of the other eight classifiers. The accuracy of Naive Bayes is 51.92%, while that of SVM is 70.13%. K-NN has the highest accuracy level of all with 89.25%. The best accuracy for this project K-NN accuracy.

APPENDIX

SAMPLE CODE

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline

from google.colab import files
uploaded = files.upload()

df = pd.read_csv('Eyedefects - KNN (3).csv')

df

df_data = df.copy()

df_scaled = df_data.copy()
col_names = ['Age', 'Target', 'Spend Hours']
features = df_scaled[col_names ]

from sklearn.preprocessing import MaxAbsScaler
scaler = MaxAbsScaler()

from sklearn.preprocessing import StandardScaler

dfs = df.copy()

import seaborn as sns
import matplotlib.pyplot as plt

dfd = df_data.copy()
dfd

import seaborn as sns
import matplotlib.pyplot as plt
```

```
df1 = dfd.drop(columns = ['Eye Strain','Eye Pain'])

f = sns.pairplot(dfd, hue='Target')


label = np.array(df.iloc[:,-1])
label

from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(df1, label, test_size=0.3)

from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=15)
knn.fit(x_train, y_train)
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
metric_params=None, n_jobs=None, n_neighbors=15, p=2, weights='uniform')
# we considered female as 0 and male as 1

KNeighborsClassifier(n_neighbors=15)

pred = knn.predict(x_test)

from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=7)
knn.fit(x_train,y_train)
y_pred_knn=knn.predict(x_test)


y_pred_knn.shape


score_knn = round(accuracy_score(y_pred_knn,y_test)*100,2)


print("The accuracy score achieved using KNN is: "+str(score_knn)+" %")

from sklearn import svm


sv = svm.SVC(kernel='linear')
```

```
sv.fit(x_train, y_train)

y_pred_svm = sv.predict(x_test)

y_pred_svm.shape
score_svm = round(accuracy_score(y_pred_svm,y_test)*100,2)

print("The accuracy score achieved using Linear SVM is: "+str(score_svm)+" %")
```

Annexure I

Questionnaire

Data for Mini project to "Eye disease prediction among corporate employees using machine learning techniques"

Name :

Age :

Gender :

Job Role :

No.of year experience in IT field :

Spending time with system :

Opinion Relating to Various Factors of Accidents

1- Rare 2- Often

3- Regular 4- No

S.No	Details	Rare	Often	Regular	No
I	**Eye Strain**				
1.	Eye Sore experienced by the individual				
2.	Eye Tired experienced by the individual				
3.	Eye Burning experienced by the individual				
4.	Itching eyes experienced by the individual				
5.	Headache experienced by the individual				
II	**Eye Pain**				
	Eye pain experienced by the individual				
III	**Burning Sensation**				

	Burning Sensation experienced by the individual				
IV	**Double Vision**				
	Double vision experienced by the individual				
V	**Blurring Of Vision**				
	Blurring of vision experienced by the individual				
1.	Long Sightedness				
2.	Shortsightedness				
VI	**Frequent Watering**				
	Frequent Watering experienced by the individual				

Annexure II

Un-Structured Data Obtained from Questionnaire

- **Questionnaire is collected from 205 persons.**
- **205 IT employees have responded to the Questionnaire and it is listed in a formatbelow.**
- **“0” is unfilled value from the respondents and it is replaced by using mean by colab.**

	A	B	C	D	E	F	G	H	I	J	K	L
1	Name	Age	Gender	Job Role	No. of years experience	spending hours	Eye Strain	Eye Strain Level	Eye Strain Grade	Strain_Reg	Strain_Reg	Eye Pain
2	Gowtham	23	Male	Maintenance production Supporter	1	8 - 12 hours						
3	Saravana Kumar	23	Male	Developer	1.4	8 - 12 hours						
4	BIJOY B	25	Male	product Owner	4	8 - 12 hours	Headache	Often	2			Often
5	KISHORE	23	Male	Developer	1	5 - 8 hours	Tired	Rare	1			Rare
6	KUMARESH K	21	Male	Developer	1	less than 5 hours	Tired, Burning	Rare	1			No
7	ARAVINDHAN A	21	Male	Tester	1	8 - 12 hours						
8	ISWARYA K	22	Female	Developer	1	8 - 12 hours	Itching eyes, Headache	Often	2			No
9	HARISH ADITYAA G	22	Male	Developer	1	less than 5 hours	Tired, Itching eyes, Headache	Regular	3	High	3	Regular
10	Gopala Krishnan	25	Male	Maintenance production Supporter	1	8 - 12 hours	Sore, Tired, Burning, Itching eyes, Headache	Often	2			Rare
11	KAMALESH PRIYAN A P	22	Male	Developer	4	5 - 8 hours	Tired, Headache	Often	2			Rare
12	Karnan	55	Male	product Owner	3	5 - 8 hours	Sore, Headache	Rare	1			Often
13	Deva	23	Female	product Owner	6	8 - 12 hours	Burning, Itching eyes, Headache	Regular	3	High	3	Regular
14	Agnus	35	Female	Business Analyst	11	8 - 12 hours	Burning, Headache	Regular	3	High	3	Regular
15	Kalai	22	Male	Quality Assurance	1	5 - 8 hours						
16	Gopi	21	Male	Developer	10	less than 5 hours	Tired, Itching eyes, Headache	Often	3			Often
17	SNEKA	23	Female	Developer	1	8 - 12 hours	Tired, Itching eyes, Headache	Regular	3	Low	1	Often
18	Suba	23	Female	Developer	1	8 - 12 hours						
19	BALA	22	Male	Tester	2	less than 5 hours	Sore, Burning, Itching eyes, Headache	Often	2			Often
20	KAMALESH	28	Male	Project Team	3	5 - 8 hours	Tired	Rare	1			Rare
21	KOWSALYA K	25	Female	Project Team	2	8 - 12 hours	Tired, Burning	Often	2			Rare
22	Rathinasamy	68	Male	product Owner	27	8 - 12 hours	Tired, Headache	Often	2			No
23	Akash	28	Male	Developer	8	greater than 12 hours	Burning, Itching eyes, Headache	Often	2			Often
24	Kandan. S	54	Male	Maintenance production Supporter	20	less than 5 hours						
25	ELAKKIYA	23	Female	Developer	2	8 - 12 hours	Burning, Headache	Often	2			Rare
26	JEGADEESH	22	Male	Tester	1	8 - 12 hours	Tired, Itching eyes, Headache	Often	2			Rare
27	Palanisamy R	42	Male	Maintenance production Supporter	15	8 - 12 hours	Headache	Rare	1			Rare
28	Janaki R	21	Female	Developer	1	5 - 8 hours	Headache	Regular	3	Moderate	2	No
29	Lokesh	21	Male	Developer	2	greater than 12 hours	Tired, Itching eyes, Headache	Often	2			Regular
30	DHARUN RAJ G	22	Male	Business Analyst	1	5 - 8 hours	Tired, Headache	Regular	3	High	3	No
31	Balakumar. P	50	Male	product Owner	1	5 - 8 hours	Tired, Itching eyes	Often	2			Rare
32	Dhava	22	Male	Tester	2	5 - 8 hours	Burning	Rare	1			Often

1	Strain_Reg	Strain_Reg	Eye Pain	Eye pain G	Eyepain_R	Eyepain_R	Burning Se	Burning Se	BS_Regula	BS_Regula	Double Vis	Double Vis	DV_Regula	DV_Regula	Bluring of	BOV_grade	Bluring of	BOV_Regu	BOV_Regu	Frequent V	Frequent V	FW_Regula	FW_Regula
2																							
3																							
4			Often	2			Rare	1			No	0			Regular	3	Longsighte	Moderate	2	No	0		
5			Rare	1			Often	2			No	0			No	0	Longsightedness			No	0		
6			No	0			Rare	1			No	0			Regular	3	Longsighte	Moderate	2	No	0		
7																							
8			No	0			Rare	1			No	0			No	0				Often	2		
9	High	3	Regular	3	High	3	Rare	1			Regular	3	High	3	Regular	3		Low	1	Regular	3	Moderate	2
10			Rare	1			Rare	1			Often	2			Regular	3	Longsighte	Moderate	2	Regular	3	Low	1
11			Rare	1			Often	2			Rare	1			Rare	1	Longsightedness			Often	2		
12			Often	2			Often	2			No	0			Often	2	Longsightedness			Regular	3	Low	1
13	High	3	Regular	3	High	3	Often	2			Regular	3	Moderate	2	Rare	1	Longsightedness			Often	2		
14	High	3	Regular	3	Moderate	2	Often	2			Rare	1			Regular	3	Longsighte	High	3	Rare	1		
15																							
16			Often	2			No	0			No	0			Often	2	Longsightedness			Often	2		
17	Low	1	Often	2			Regular	3	Moderate	2	Rare	1			Regular	3	Shortsight	High	3	Rare	1		
18																							
19			Often	2			Often	2			Often	2			Often	2	Longsightedness			Often	2		
20			Rare	1			No	0			No	0			Regular	3	Longsighte	Low	1	Rare	1		
21			Rare	1			Rare	1			Rare	1			Rare	1	Longsightedness			Often	2		
22			No	0			Rare	1			Regular	3	Moderate	2	Regular	3	Longsighte	Moderate	2	Often	2		
23			Often	2			Rare	1			No	0			Often	2	Longsightedness			Often	2		
24																							
25			Rare	1			Often	2			Rare	1			Regular	3	Longsighte	Moderate	2	Often	2		
26			Rare	1			Rare	1			Often	2			Often	2	Shortsightedness			Regular	3	Low	1
27			Rare	1			Rare	1			No	0			No	0				Rare	1		
28	Moderate	2	No	0			Rare	1			No	0			No	0	Shortsightedness			Rare	1		
29			Regular	3	Moderate	2	Often	2			Regular	3	Moderate	2	Often	2	Shortsightedness			Often	2		
30	High	3	No	0			Regular	3	Moderate	2	No	0			No	0	Longsightedness			Regular	3	High	3
31			Rare	1			Rare	1			Rare	1			Rare	1	Longsightedness			No	0		
32			Often	2			No	0			No	0			No	0				Rare	1		

Screenshots for the dataset

175	AjayKumar R U	21	Male	Business Analyst	1	5 - 8 hours						
176	SENTHIL	27	Male	Quality Assurance	5	8 - 12 hours	Tired	Rare	1			Often
177	Sundaramoorthi	29	Male	Sales Team	5	5 - 8 hours	Tired, Headache	Often	2			Regular
178	Sandhya	22	Female	Tester	1.5	8 - 12 hours	Tired, Headache	Often	2			No
179	Nivetha v	23	Female	Business Analyst	2	5 - 8 hours	Tired	Rare	1			Rare
180	NAVEENCHANDAR	24	Male	Developer	0.2	8 - 12 hours						
181	Prasath Ganesh	35	Male	product Owner	10	greater than 12 hours						
182	Kadhirvel	34	Male	Business Analyst	12	5 - 8 hours						
183	Manoj S	33	Male	Tester	10	5 - 8 hours	Headache	Regular	3	Moderate	2	Regular
184	Kiran kumar	26	Male	Tester	3	5 - 8 hours	Headache	Often	2			Often
185	Sureshkanna J	28	Male	Developer	5	8 - 12 hours						
186	J.Gomathipriya	27	Female	Sales Team	5	8 - 12 hours						
187	Gunasekaran J	37	Male	Quality Assurance	2	5 - 8 hours						
188	Mr. S. Dharani krishna	20	Male	Project Team	1	8 - 12 hours	Tired, Burning, Headache	Rare	1			No
189	SANDHIYA	21	Female	Business Analyst	1	5 - 8 hours						
190	HAMETHA	22	Female	Tester	1	5 - 8 hours	Headache	Rare	1			Often
191	Raji	21	Female	product Owner	2	5 - 8 hours						
192	Ananjan	22	Male	Project Team	1	8 - 12 hours						
193	Akshaya A M	22	Female	Business Analyst	1	5 - 8 hours						
194	HANSIKA	22	Female	Business Analyst	1	5 - 8 hours	Itching eyes, Headache	Often	2			Rare
195	KUMAR P	52	Male	Maintenance production Supporter	24	greater than 12 hours	Itching eyes, Headache	Regular	3	High	3	Often
196	SIVA PALANI MURUGAN	21	Male	Project Team	2	5 - 8 hours	Itching eyes, Headache	Often	2			Often
197	sudalai sivam	42	Male	Developer	15	5 - 8 hours	Itching eyes, Headache	Often	2			Often
198	Jack	55	Male	Project Team	12	less than 5 hours	Sore, Tired, Burning	Regular	3	High	3	Regular
199	karthick	55	Male	product Owner	16	8 - 12 hours						
200	DHARANI R	22	Female	Tester	1	5 - 8 hours	Burning, Headache	Often	2			No
201	ramakrishan	48	Male	Sales Team	8	5 - 8 hours						
202	SAKTHI R	21	Male	Developer	1	5 - 8 hours	Tired	Rare	1			No
203	Visali	22	Female	Project Team	2	5 - 8 hours						
204	Gokul	23	Male	Maintenance production Supporter	1	less than 5 hours						
205	Arthi	22	Female	Project Team	3	8 - 12 hours	Tired	Often	2			Rare

	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF
75																							
76			Often	2			Often	2			Rare	1			Often	2	Shortsightedness			Rare	1		
77			Regular	3	High	3	No	0			No	0			Regular	3	Longsighte	Moderate	2	Regular	3	High	3
78			No	0			Rare	1			Rare	1			Regular	3	Longsighte	Moderate	2	No	0		
79			Rare	1			Rare	1			No	0			Rare	1	Shortsightedness			Rare	1		
80																							
81																							
82																							
83	Moderate	2	Regular	3	Moderate	2	Rare	1			No	0			No	0	Longsightedness			No	0		
84			Often	2			Often	2			Rare	1			Rare	1	Shortsightedness			Often	2		
85																							
86																							
87																							
88			No	0			Often	2			No	0			No	0	Longsightedness			No	0		
89																							
90			Often	2			Rare	1			No	0			No	0	Longsightedness			No	0		
91																							
92																							
93																							
94			Rare	1			Often	2			Rare	1			Often	2	Longsightedness			Rare	1		
95	High	3	Often	2			No	0			No	0			Regular	3	Shortsight	Moderate	2	Regular	3	High	3
96			Often	2			Regular	3	Moderate	2	Often	2			No	0	Shortsightedness			Regular	3	Moderate	2
97			Often	2			Regular	3	High	3	No	0			Regular	3	Shortsight	Moderate	2	Regular	3	Low	1
98	High	3	Regular	3	High	3	Regular	3	High	3	Regular	3	High	3	Regular	3		High	3	Regular	3	High	3
99																							
00			No	0			Often	2			Rare	1			Rare	1	Longsightedness			Rare	1		
01																							
02			No	0			Rare	1			No	0			No	0				No	0		
03																							
04																							
05			Rare	1			Rare	1			Often	2			Regular	0	Longsighte	Moderate	2	Often	2		

Screenshots for the dataset

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