*This is a*[*dynamic list*](https://en.wikipedia.org/wiki/Wikipedia:WikiProject_Lists#Incomplete_lists)*and may never be able to satisfy particular standards for completeness. You can help by*[*adding missing items*](https://en.wikipedia.org/w/index.php?title=List_of_accidents_and_disasters_by_death_toll&action=edit)*with*[*reliable sources*](https://en.wikipedia.org/wiki/Wikipedia:Reliable_sources)*.*

This is a **list of accidents and disasters by death toll**. It shows the number of fatalities associated with various [explosions](https://en.wikipedia.org/wiki/Explosion), [structural fires](https://en.wikipedia.org/wiki/Structure_fire), [flood disasters](https://en.wikipedia.org/wiki/Flood), [coal mine disasters](https://en.wikipedia.org/wiki/Mining_accident), and other notable accidents caused by the effects of [negligence](https://en.wikipedia.org/wiki/Negligence) of the human race connected to improper [architecture](https://en.wikipedia.org/wiki/Architecture), [planning](https://en.wikipedia.org/wiki/Urban_planning), [construction](https://en.wikipedia.org/wiki/Construction), [design](https://en.wikipedia.org/wiki/Design), and more. Purposeful disasters, such as [terrorist attacks](https://en.wikipedia.org/wiki/List_of_terrorist_incidents), are omitted; those events can be found at [List of battles and other violent events by death toll](https://en.wikipedia.org/wiki/List_of_battles_and_other_violent_events_by_death_toll).

While all of the listed accidents caused immediately massive numbers of lives lost, further widespread deaths were connected to many of these incidents, often the result of prolonged or lingering effects of the initial catastrophe. This was the case particularly in such cases as exposure to [contaminated](https://en.wikipedia.org/wiki/Contamination) air, [toxic](https://en.wikipedia.org/wiki/Toxicity) [chemicals](https://en.wikipedia.org/wiki/Chemical_substance) or [radiation](https://en.wikipedia.org/wiki/Radiation), some years later due to [lung damage](https://en.wikipedia.org/wiki/Respiratory_disease), [cancer](https://en.wikipedia.org/wiki/Cancer), etc. Some numbers in the table below reflect both immediate and delayed deaths related to accidents, while many do not.

No matter how much we strive to make our domestic environment as safe as possible, accidents at home can still happen - even in the most conscientious of households.

When it comes to the health of our families, especially for those with young children, it makes sense to know exactly what to do if these common scenarios do occur.

At Benenden, we want to help increase your confidence in dealing with minor issues of health and safety in the home and we’re on hand to give members reassurance and advice whenever it’s needed.

Here are 10 of the most common accidents that can happen in the home and how to deal with them:

## 1) Falling objects

When children start to move around on their own, there is an increased danger of them pulling objects down on top of themselves. Being conscious of your kids' health means making sure any trailing electrical leads, tablecloth edges and dish towels are out of reach in order to help prevent accidents happening.

## 2) Trips and Falls

A fall can affect people of all ages, but they are most common amongst the very young and the very old. Often, falling over as a child will only hurt their pride and a few soothing words is all that’s needed. However, if the person who has fallen subsequently becomes drowsy, vomits or loses consciousness, it is important to seek medical advice.

## 3) Bruises

Even a fall that isn't serious can lead to nasty bruising which can be quite painful. Applying a cold pack - or even a packet of frozen peas - to the area affected can reduce swelling. Sometimes severe bruising can hide more serious issues such as broken bones, so if there is a great deal of continuous pain or movement of a limb is very restricted or impossible, once again professional help should be sought.

## 4) Sprains

A sprain is when a ligament, which connects parts of a joint, is stretched, twisted or torn. Knees, ankles and wrists are the most common parts of the body affected. If this occurs, apply an ice pack from your first aid kit, rest the affected area and give it time to heal.

## 5) Cuts

Any cut means that there will be some blood, and this can be one of the most difficult things involved in first aid for children. Apply pressure to stop the bleeding and apply an antiseptic to the area. Assessing the situation is important, but (generally speaking) if the blood stops following pressure, it is likely to be a minor cut that will not need stitches.

## 6) Burns

Hot drinks cause most burns and scalds to children under the age of five and, of course, children should be kept a safe distance away from open fires, cookers, irons, hair straighteners and matches, as these can be dangerous too. Any burn should be held under cold running water for ten minutes and then assessed. Having a clean plastic bag or cling film in your first aid kit can be an ideal way to cover burns to keep them clean and help them to heal.

## 7) Choking

Children can often have a fascination with putting objects in their mouth and swallowing them, meaning that choking is a common hazard. If you cannot dislodge the object promptly, then call 999 immediately.

## 8) Poisoning

Most poisoning incidents involve medicines, household products and cosmetics around the house. It is important, therefore, to keep anything that might be dangerous if swallowed well out of reach of children as an essential part of first aid in the home.

## 9) Glass-related injuries

Broken glass can cause serious cuts and so use of the material around the home in furniture or fittings should be carefully considered if you have a young family. Make sure doors, tables and shelving conform to British safety standards.

## 10) Drowning

Young children can drown in very shallow water, so should be supervised at all times when near it. This includes ornamental garden ponds,

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**Road accidents:**

Accidents happen every day. Road accidents can occur for a variety of causes, including driving at fast speeds, adverse weather conditions, and drunkenness. One of the main issues and the main contributor to accidents all around the world is drowsy driving. A drowsy driver is often one who feels lethargic, has difficulties concentrating, and has tired eyes. Drowsy driving, also known as driver fatigue or tired driving, is the act of operating a motor vehicle while feeling tired, sleepy, or weary. Drowsiness was described as "The need to fall asleep" by (Colic 2014). Human brain is affected by lack of sleep. The driver's performance gradually deteriorates as a result of tiredness. When a motorist starts to nod off

The major causes of sleepiness might include irregular sleeping habits, lengthy driving hours, stress, and disturbed sleep. Most commercial drivers and shift employees who are travelling home from the office are exhausted and sleepy when they are behind the wheel. Even shift-worker taxi drivers and those on medication or with little sleep are more likely to experience drowsiness while operating a vehicle. Drivers of automatic vehicles fall asleep more frequently than manual drivers.

Road accidents seriously affect the nation's human capital and economy. WORLD BANK research claims that fatalities and injuries from vehicle accidents have an impact on long-term economic prospects since the wounded workforce may not be able to work or may die from a serious injury, which lowers production.

Almost three quarters (72%) of those questioned said they had experienced a mental health issue following their accident - a third said they had been stressed, one in five struggled to sleep, and a third suffered anxiety.

Other mental health issues which people experienced included suffering from depression (18%), having nightmares (13%), panic attacks (13%), and experiencing PTSD (7%).

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Driver drowsiness detection is measured in three categories as proposed by (Ramzan, Khan et al. 2019). The following are the different measures that help in collecting the data for detection drowsiness of the driver.

DRIVERS:

Drowsiness detection in vehicle-based measures uses a variety of characteristics, including lane detection, accelerator pattern, and steering wheel adjustments. Data is gathered via a variety of in-car sensors. The driver's emotions are calculated based on lane departure and steering angle variations.

The present systems typically use lane deviation to identify tiredness, however this parameter is impacted by a number of external factors, including weather, road markings, and illumination. More specifications, such control systems and vehicle layout, are needed for vehicle-based measurements. The cost of developing this strategy for real-time use is high. Furthermore, a driver's drowsiness cannot be inferred only from the vehicle's characteristics because lane departure might also be caused by drug and alcohol usage.

Measures:

The characteristics taken into account for determining drowsiness levels include the driver's yawning, the ratio of eyes blinking, and facial movements and head posture. Driver emotion is assessed based on the driver's mouth, eyes, and head posture. This metric is more effective at identifying driver sleepiness despite certain limitations such illumination issues and the impact of environmental factors.

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Physiological measurements are invasive, inexpensive, and simple to use in the present. Early signs of sleepiness can be identified using electroencephalogram, pulse charge, coronary rate, brain waves, and heart rate. The emotion of the driver is identified using the driver's heartbeat, pulse rate fluctuation, and ECG. It is necessary to attach a variety of sensors and electrodes in order to assess driver sleepiness. Drivers are reluctant to have electrodes and sensors attached to them for an extended period of time, thus they do not accept this intrusive procedure.

On the other hand, data privacy is a crucial non-technical problem for creating a sleepiness detection algorithm. Data privacy concerns emerge when drowsiness detection uses the driver's personal information, such as behaviour and facial expressions. The database will collect and preserve information on the driver's ethnicity, his facial expressions, and his behavioural condition. An crucial element to consider is how this captured data is used and kept.

The expense of developing, maintaining, and using the model in real-time is another significant difficulty in its design. If the sleepiness detection model's production and maintenance costs are too high, it cannot be used in real-time.

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Technology has undergone a significant transformation as a result of recent advances in computer vision and the use of deep learning algorithms. When it comes to spotting driver sleepiness, deep learning algorithms surpass practically all machine learning model techniques. The non-intrusive strategy is practical. as the driver is not bothered by it and the driver's body is not connected to the sensors and poles. Convolutional Neural Networks (CNN) based models are being used for feature extraction and emotion detection in numerous applications, including the identification of tiredness using behavioural data. When CNN is included in the model, the pre-processing of the data and the classification process take extra time since CNN needs a lot of data to categorise and identify sleepiness.

Additionally, CNNs are unable to handle connections between pixels over large distances. Since convolution was used for the bulk of CNN layers, data is lost during convolution. Additionally, applying CNN techniques to identify a driver's expression in real time is quite difficult due to the variety of eye states and other environmental factors. Constantly having a large number of parameters, convolutional neural networks are also incredibly costly to train.

In order to reduce accidents, a low-cost drowsiness detection model that improves the accuracy of detecting driver tiredness is required. This study suggests a convolution-free hybrid model that makes use of a variety of data, including the driver's pupil size, mouth position, and eye state.

The films are taken using a smart phone and a smart watch, and the driver's heart rate is extracted in real-time. A real-time data collection established by the University of Texas at Arlington for drowsiness detection (UTA-RLDD) 2021) as well as a YAWNDD dataset will be utilised for testing and validating the suggested model on huge amounts of data. The model's ultimate objective is to routinely identify the driver's emotions and avoid accidents.

ML

Videos containing the gathered data are initially transformed into frames and HOG The extraction of features like the eye area and mouth region is carried out using Dlib software, and the histogram of an Oriented gradient is utilised to recognise the driver's face. The driver's pulse rate will be extracted from a smart watch, and those traits, along with behavioural ones, will be supplied to a hybrid. To assess the driver's mental state, use the Long-Short Term Memory (LSTM) - Vision Transformer model.

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ML

Electroencephalograms (EEG) and electrooculograms (EOG) are two of the finest methods for determining the degree of sleepiness, according to a technique presented by (Grace, Byrne et al. 1998). For the purpose of analysing heart rate, the driver's head and torso are fitted with electrodes and several sensors. A RNN architecture is fed the collected data in order to analyse the driver's emotions. The most accurate results may be obtained by employing a straightforward mathematical computation to identify tiredness using EEG features. However, because this technology necessitates placing electrodes near the driver's eyes and all around his or her head while they are driving, drivers did not readily accept it.

To get around these restrictions, a camera is placed in front of the driver and continually records him. A model to identify driver intoxication has been created (Chai 2019) based on the state of the steering wheel. To identify sleepiness, many characteristics are assessed, including steering holding time, angular velocity, steering angle, and angel ratio, among others. Support Vector Machine (SVM), Multilevel Ordered Logit (MOL), and Back Propagation (BP) approaches are utilised in conjunction with those parameters to pre-train the mode and analyse the driver's emotions on a regular basis to determine if they are steady or getting tired.

 suggested a technique for narcolepsy and micro sleep detection. Face and eye identification, feature extraction, single eye extraction, and tiredness detection are the technique's three most important elements. It makes use of a Raspberry Pi and a web camera to monitor the driver's eyes, and tiredness is identified by monitoring the rate at which blinks occur. It should be more pleasant for the driver because it is more portable. The Viola-Jones method, which is utilised in this instance to discover faces, may be used to find other objects as well. Therefore, it can affect the system's accuracy.

When thinking about image processing, it is essential to identify facial features, such as the lips, eyes, and other facial objects. The vast majority of research employed a variety of methodologies to detect face regions and objects. Researchers (Zhang, Su et al. 2017) recommended the "Ada Boost" technique (adaptive boosting) together with regression analysis as a model for extracting face landmarks. According to research by Weili, Xia et al. (2011), the adaptive boosting strategy makes it harder to distinguish between the eyes. Because of this, they accurately identified face features and eyes using the "Ada Boost" and "Blob Detection" algorithms, and then employed the validation approach to confirm eye recognition. They also used NIR filters to lessen feature extraction errors brought on by variable environmental parameters, such as illumination.

Vidhu Valsan (Valsan, Mathai et al. 2021) created a non-intrusive tiredness diagnosis method using eye-tracking and picture processing. The average eye-opening stage, blink frequency, blink duration, percentage of closed eyelids, opening speed, and closing velocity are the six drowsiness detection measures. Several computer vision techniques are utilised for drowsiness detection to determine the amount of tiredness. It primarily uses the Haar cascade classifier and the Viola Johnes technique for face detection.

Monitoring and analysing the area around the mouth is the basis for yawn detection. Luwang used the picture interpolation approach to detect the nasal centre and jaw on the face. The driver's yawn was then determined by measuring the vertical distance between the chin and nostril midway. The sleepiness detection approach proposed by Saurav et al. [38] uses the mouth aspect ratio (MAR) to assess mouth condition and is employed in a variety of applications. The Viola-Jones algorithm was used by Omidyeganeh [37] et al. to recognise the face and mouth and to measure changes in the mouth..

detection process. In 2010, Chai, T. Y., Woo et.al [1] proposed an EEG signal-based model. The signals will change according to the emotions experienced. Signals are impacted by the variety of stimuli. At the time, this approach had a high categorization rate. 2015 saw Lee, K. W. Yoon suggested a model based on behavioural measurements in et. al [3]. where he employed CNN and temperature sensors to look for signs of sleepiness. In his work, he provides a brief explanation of the costs associated with reckless driving as well as recommendations for accident avoidance strategies. Numerous marvels in the field of image processing have emerged with the debut of computer vision and deep learning techniques. A contact-free technique termed the Dricare method was presented in 2019 (Deng and Wu 2019), and it addresses three major obstacles to sleepiness level detection. first by taking into account the driver's height and various head positions in a video. At this moment, face postures are continuously observed. Convolutional Neural Networks were utilised to extract critical facial features since the driver's eyes and lips are crucial for identification. They identified the amount of tiredness in the driver based on the PERCLOSE approach developed by Grace, Byrne, and colleagues in 1998. The suggested approach produced the highest accuracy, however it is ineffective when a driver is wearing eyeglasses.

With the help of a smartphone, Chatterjee and Sharma suggested a model that can identify driving tiredness by routinely observing the driver's eyes. In order to identify the eye condition, Chatterjee and Sharma (2018) employed facial features. The alarm system is triggered if the driver's eyes are closed. have created a real-time model that extracts the facial characteristics of the driver and determines their emotional state using Dlib and OpenCV. Data is captured using a smartphone, and OpenCV is used to identify aspects including the condition of the lips, head movements, and eyes. This model has produced superior outcomes in identifying tiredness. In this research, this programme is used to extract features from behavioural metrics. based on behaviour, hand and head motions, facial expressions, and facial expressions. (Dua, Singla et al. 2021) suggested a novel approach to use RGB footage of the driver to identify tiredness.

The authors offer a method for monitoring driver weariness using bio signals picked up by bio sensors (Lee and Chung 2012). It is not intrusive, but it alerts people to changes when they are dealing with different illnesses or harmful situations. Ocular measures are the most accurate and non-intrusive method of drowsiness detection. This tactic involves monitoring the driver's eyesight and using computer vision algorithms to determine how fatigued they are.

(Bharadwaj, CN et al. 2019) created and applied a method to identify fatigue; they used a camera to take pictures and watch the driver's eyes to determine if the driver was drowsy or not. The model was made by (Omidyeganeh, Shirmohammadi et al. 2016). To recognise the mouth and determine each person's level of tiredness, a smart camera was employed. There has been a suggestion of a way to recognise tiredness by (Huynh, Park et al. 2016). Gradient boosting was used to identify tiredness, 3D CNN was utilised to extract face characteristics, and semi-supervised learning was applied to enhance system performance.

The transformer architecture was motivated by the success of the attention mechanism vas(). This design is based on the attention mechanism, however unlike the attention mechanism, which only employs one attention layer, it uses many head mechanisms. In Natural Language Processing, the suggested model did well (NLP). Transformers were used in emotion identification tests, and the results were great. It surpassed many other tasks.

A hybrid model was created by Yuan et al. (19) that combines CNN-Vision transformer for feature extraction and CNN-Emotion Analyzer for driver emotion analysis. This approach produced superior outcomes and is reliable under many circumstances. Similar hybrid CNN-Vision transformer technology was developed by Carion[20], however his major emphasis was on the use of attention mechanisms to enhance target recognition. He gave it the moniker DETR. After that, Google created a transformer model without altering the transformer's original design and used it in computer vision in lieu of CNN. In the majority of situations, they have produced excellent outcomes and outperformed CNN models. According to Yuan et al. [22], adopting straightforward labelling ViT can increase training effectiveness.  research has paved the way for early sleepiness detection with a variety of ways to avert mishaps. We may infer from the data that behavioural and physiological strategies both produce accurate results in identifying sleepiness. The hybrid CNN-Vision transformer model has shown superior results when used in real-time applications, however it performs poorly when used to big datasets. In order to improve accuracy, this study suggests the development of a novel hybrid LSTM-Transformer model that analyses driver mood based and physiological data.

A smartphone records the driver's face while they are driving and converts the videos into frames. The software then performs a video analysis to look for signs of exhaustion and sleepiness, as well as to determine drowsiness level. The primary components that should be analysed at this stage are face tracking, level of weariness, and identification of important facial features based on yawing and eye closure. A smart watch captures heart rate and pulse rate of the driver regularly. Based on the above parameters the state of driver is analysed and a voice alert notification will be raised if drowsiness is detected. If the output of the model predicts that the driver is drowsy or in unstable state then the system will instantly alert the driver and tries to bring his attention back so that he/she may decide whether to take a break or continue driving.

This study examined the driver's sleepiness utilising a variety of drowsiness-related data sources. These measurements are made by observing the driver's actions while they are experiencing various emotional states.

In this study, the UTA-RLDD and YawnDD datasets are used to obtain the necessary data for the behavioural analysis. Real-time video recording is used to capture the data, which is then saved in the dataset's movies. Smartphones have been used to capture the motions of the face, lips, and eyes as well as facial expressions. The mobile phone is positioned in front of the user so that a clear image of their face can be obtained, allowing for the recognition of their emotions. This study examined the driver's sleepiness utilising a variety of drowsiness-related data sources. These measurements are made by observing the driver's actions while they are experiencing various emotional states.

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The dataset contains 180 RGB videos. Each 10-minute video is divided into three categories: alert (zero), low vigilance (five), and drowsy (10). The individuals themselves assigned labels to the dataset based on the mental state they believed themselves to be in. This mimics the change from being awake to displaying some signs of weariness and then to being drowsy. For cross-validation, the dataset is further partitioned into 6 folds with each participant. The data related to drowsy driving is only utilised for this system.

**DATA:**

Pre-processing is essential for any type of data to filter and remove noise due to low capturing quality. Every captured data has to undergo pre-processing stage as the image quality may be degraded due to light transmission properties such as scattering and absorption and environmental characteristics such as light changes, weather conditions, and hue are more or less prominent while vehicles move or if an unclear rigid scene, an unidentified hue, or poor light sensitivity is captured(Padmavathi, Shanmugapriya et al. 2011).

The real time videos are obtained from the dataset and initially, the videos are converted into frames and size of the frames are adjusted. As the acquired data is in 3D value the data should be resized and can be converted into grey scale image in order to reduce the complexity. Grayscale processing is performed on frames extracted from a video sequence. Grayscale pictures are just a reduction in complexity from 3D value to 1D value. As the videos are recorded in different