Predicting Wind Energy Resources and Minimizing its Effects on Birds

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Abstract

Recently, the world has seen widespread adoption of renewable energy resources. This can be achieved by using a variety of renewable energy sources, out of which wind energy is the most popular all over the world. Fossil fuels emit a lot of carbon emissions which contributes to global warming and nowadays they are expensive too. Future energy sources are renewal energy which will be the primary focus of energy predictions. Over the past decade, wind energy generation has gradually increased with the help of machine learning technologies which are constantly developing. Wind energy prediction is the main task because the energy supply-demand should be maintained by the energy grid if nations are moving toward global energy. Time series analysis will help to achieve wind energy prediction goals. On the one hand, wind turbines provide a renewable source of energy, but on the other hand, while the blades are in operation, several bird species collide with them and die, doing significant harm to the bird species. Therefore, This research work focuses on developing novel solutions for wind energy predictions and bird life preservation. In this work, we will integrate wind energy prediction with bird identification to better understand wind energy prediction and protect bird life.

1 Introduction

1.1 Background

Climate change is a big concern globally seeing the impact of global warming caused by non-renewable sources. Solar energy, hydroelectric energy, bio-energy, and wind energy are some of the renewable green energy alternatives. Wind energy has rapidly emerged and wind turbines generate electrical energy from the wind. The pros of wind turbines are it is cost-effective, and beneficial for remote areas such as farmers with a clean source of power while corns turbine blades produce noise and have a more significant impact on local wildlife. The wind turbine can injure or kill birds upon collision with the edges. Some of the bird species have been endangered because their population than the local population can reproduce is declining. Therefore, in order to minimize such an effect, the process of detecting the number of birds and locating them in an image is informative to automate.

1.2 Importance

As the demand for wind energy is increasing in the last few decades which result in an increase in power grid and wind turbine installation is increasing rapidly but they are not able to utilize wind energy. The grid's consumption and power generation data will be out of balance due to random power generation. In order to balance it grid limit the energy supply and wastes a lot of wind energy. We need to have an accurate power prediction model for wind speed which can help the grid to know at what time they will be producing more wind power it will be safe for the power grid and utilize the wind. As wind depends on the weather, which is also very unstable. As wind power is becoming more stable and reliable wind power prediction is paid more attention.

Wind energy is one of the best cost-efficient, effective, and environmentally friendly sources of sustainable and renewable energy. The wind is a renewable and free source of energy and it does not have any effect on the environment. Due to wind power, many wind plants have been installed where wind flow is good. Which become a business on a large scale of electricity production due to which natural resources are saved and environment friendly. Therefore wind energy prediction plays an important role in today's world because everything is dependent on power. There are various factors that may affect wind energy such as fluctuating weather conditions like temperature, rain, and wind. Wind speed determines how much power can be generated by the turbine. Wind energy is not constant throughout the day and does not have the same pattern of wind flow. we will be using time series analysis to find out the best time for power prediction.

In the past few years, (Deep neural networks) DNN is built on the basis of machine learning and archived great success in time series prediction. It accurately represents the facts and minimizes manual design features. Then (Recurrent neural network) RRN , an updated version of DNN with hidden layers that mix old data with fresh data. Though it gives good accuracy it works on data with a short time span. When it comes to large time spans it does not work well so this (Long short-term memory) LSTM model was introduced which can deal with big data and recall all past data from its neural network layer. In this research, LSTM is used for wind energy prediction.

The aim of this research is to produce more energy during the peak hour of the day with a low running cost for each wind turbine. Numerous bird species are in danger of extinction. Because of the high wind speeds near the wind farm, birds flying close to wind turbines run the risk of being struck by the blades because they cannot see the wind turbines properly when they are in operation. Another model that will aid in preserving natural bird habitat has been developed in this study as a means of overcoming this. When a wind turbine is in operation and birds are flying close to it, the birds don't want to hit the turbine's blades because the turbine will be stopped at that moment and the birds can easily pass through it.

There are several main problems associated with real-life images, such as blurry images due to camera instability, or due to poor weather conditions. Therefore, areal images with the different flying orientations of birds and with different birds' sizes are captured for more accurate information. The data set has been made by collecting a variety of shots of the birds from different bird habitats on the farmland and close to lakes. Deep learning is being applied in many fields such as object detection because of its high precision and available processing power. The data sets are employed with object detection models to analyze the areal image data with average precision and high computing speed. Object detection is mainly divided into stages: single-stage and two-stage detectors. Single-stage, such as Single Shot Multi-Box Detector (SSD), You Only Look Once (YOLO) compute bounding boxes and classification simultaneously while two-stage such as Fast R-CNN, Faster R-CNN, and Region-based Convolutional Neural Network (R-CNN) (Hong et al. 2019) compute bounding boxes and classification sequentially. The processing of one-stage is faster than two-stage; however, accuracy and computational speed are different in these methods.

1.3 Research Question and Objective

Wind energy prediction and minimizing its effect on birds. The objective of this research is to predict wind energy to meet the energy supply-demand and save birds life that hit on wind turbine blades when they are operating.

2 Literature Review

This section examines recent research on the impact of wind farms on birds. LSTM and RNN models are used to forecast wind energy. Models for image detection like SSD, R-CNN, and YOLO are reviewed.

2.1 Wind mills effect on birds

A renewable energy source that is becoming more and more popular, is wind power. The author (Smallwood et al. 2009)researches that as it grows faster it also creates an impact on the environment particularly on bird species. Pre-construction surveys can help to lessen the impact on birds. minimize its effect on birds. Wind research areas have counted numerous bird fatalities due to collisions of birds with wind turbines and poles, so for this wind researcher has investigated and monitored live bird detection where they are planning to set a new or upgrade a new wind farm. Bird monitoring has been done for installing a new site and finding new ways to have less effect on birds. This objective is achieved by using visual scans over timed sessions which help to identify flight paths and count birds using the area, it also helps in wind turbine placement and tower height, in the last 2 decades the ratio of birds colliding with the wind turbine is more when the wind turbine is operating.

The mortality of birds at the wind farm is expressed by an annual number of fatalities per unit representing the size of the wind farm and the radius of the wind turbine blades. In reference (Smallwood 2007) gives all the data on bird death to the society about a particular wind farm and these are calculated seasonally or annually. These estimates can help researchers to see the difference between the data which can help to find the best solution of it without the loss of power generation. The estimator can compare the different site data to see how much biological impact is done. Instead of pointing out bird death caused by wind farm mortality estimates facilitate can compare the end of birds caused by wind farms with other human activities. The other factor for bird mortality may be the green field near the wind farm, especially the fruit trees which are food for many birds. The number of carcasses found during the search increased slightly, there are few birds like ravens that learn quickly of carcass availability and change their direction.

In reference to the researchers (Drewitt & Langston 2006) with the study of existing wind farms the four main pieces of evidence for the mortality of birds found to be a collision, displacement as a result of disturbance, boundary effects, and loss of habitat are discussed. Post-construction monitoring surveys are done with the rapid construction of wind farms which can take serious steps to minimize bird mortality. Mitigation measures are taken to minimize the impact. As countries are making it a target to shift toward the renewable source of energy like wind energy because of greenhouse gas emission which leads to good global climate change but wind energy also have a bad impact on wildlife. The research has summarized the potential effect of increased wind energy development from the studies of existing wind farms and what possible mitigating actions could be taken to lessen the effects.

2.2 LSTM for energy prediction

The author in reference found that (Zhang et al. 2019) fossil fuels are not matching sustainable development and the price is increasing so the world is moving toward renewable energy as it is eco-friendly. As the world is becoming digital electricity demand is increasing everything requires electricity to operate, and prediction accuracy of power is becoming accurate for the wind power grid operator. In this research, LSTM model is applied for getting better accuracy with an autoencoder which reduces the dimension of the data, makes the model good for prediction, and reduces the training time. When the simulation is run it shows that the LSTM model has better accuracy than (Super vector machine) SVM. Earlier methods which are used for power prediction are physical methods and statistical methods. These methods required accurate weather forecasting but wind speed is fluctuating very fast in short intervals of time so it does not perform well. The machine learning method is used with the SVM model for non-linear mapping.

In this research (Kusiak et al. 2013) wind energy prediction depends on the following wind speed, turbine control, hybrid power control system, Examination of condition monitoring, and defect finding. For the purpose of predicting wind speed at various time scales, statistics, physics, and data mining are studied. Methodologies and faults which affect wind energy prediction are explained.

The research (Okumus & Dinler 2016) reviews on recent power prediction and wind energy prediction are done in this paper. Fossil fuels are creating a lot of carbon emissions which cause the greenhouse effect to keep this thing in mind world is changing toward renewable sources of energy like solar and wind. Wind energy is a clean source of energy and is widely used around the world for power generation but due to the chaotic nature of wind energy forecasting is not accurate. The need for better predictions is great, and there is a lot of research being done to create better forecasting models. In this research wind speed and power generation reviews of recent papers are done in which intensive efforts for better prediction are applied and advanced machine learning techniques are used. The study prediction methods are divided into four groups pre and pro-processing, hybrid, and non-hybrid. Two hybrid methods are a combined adaptive neuron-fuzzy inference system (ANFIS) and a feed-forward artificial neural network (FNN). This combination is best for hourly predictions

2.3 YOLO for image detection

The research (Alqaysi et al. 2021) discusses YOLOv4 model which is used to improve the detection of small birds. This paper collected two datasets from two places Klim and Skagen in Denmark. Four different steps have been used to improve the accuracy of bird detection:

a Background subtraction to bootstrap data analyzing process

b Camera gain reparations

c Noise removal

d Blob detection

In this, they use three models. Model 1 uses a recent iteration of YOLO i.e., YOLOv4 which executes poorly for small birds (seem smaller in the image) which is because when the image is resized to 1024×1024 the information of small birds is lost. To address this problem Model 2 (Tilting + YOLOv4) splits the 4K image into 1920×1080 four images. Then each image is resized to 1024×1024 to feed into YOLOv4 assuming birds rarely occur at these tilting boundaries. This model failed when a bird straddle one of the tilting boundaries. Both above models failed to deal with the videos. Further, model 3 uses tilting + temporal Stacking + YOLOv4 that improves bird detection performance which not only decreases the issues due to blur and defocus of the camera but also the small image size of the bird. Model 3 achieves the highest mAP values of both datasets.

As discussed in this research (Hong et al. 2019) it is difficult to identify migratory birds during specific periods of time. Kim et al.constructed object detection models by collecting photographs from unmanned-based vehicles (UAV) which is cost-effective, reduces human working time and reduces the risk of airplane accidents. Further, target counting in aerial photographs has been performed by two methods: (1) manual and (2) automatic counting. In manual counting samples, count methods are generally used. The population of the target in the aerial counting method is estimated by measuring the perpendicular distance between the flight path and the target. However, the automatic counting method reduces labor and time through image-processing algorithms and computing systems. The automatic counting method increases the input data (number of images to detect birds across various regions) which is relatively small in manual counting. For object-detection methods, Conventional neural networks (CNN) consist of two stages that are processed sequentially (first bounding box proposal and then classification) which make it a bit slower as compared with one stage object detection method. YOLO, SSD process the bounding box proposal and the classification simultaneously. Moreover, by comparing the computing speed AP, the performance of bird detection models was verified. After the image collection labeling process id did. First, the pixel size (40 × 40 pixels) of one box corresponds to one bird is assigned. From different places, the birds' decoys were obtained. These decoys are added to aerial photograph datasets. Then the image processing i.e., image cropping and augmentation (to build a robust model), to obtain several hundred sub-images of the aerial photographs was performed. Further, feature representation is trained by a deep-learning-based detection model. Therefore, a two-stage and one-stage (YOLO) detection method is performed which is accurate and very fast. AP (area under the precision-recall) the commonly used performance index was used to evaluate the detection accuracy. Where the precision is calculated by:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

where TP (true positive i.e., number of birds correctly detected), FP (false positive i.e., number of birds incorrectly detected), and FN (false negative i.e., number of ground truth birds undetected). Finally, the testing process of bird detection is performed by a learning model. The test results show that two-stage Faster R-CNN is the most accurate and YOLO is the fastest among the different models used in this paper.

In this research (Liu et al. 2018) the blur and defocus image problems have an effect on object detection which was resolved by the YOLO network. Chen et al. use image degradation models based on the YOLOv3 neural network to train a model to improve the average precision (AP) of degraded images. 80 percent of the standard data set which includes all of the photos that underwent general degradation processing. In addition to these images to train the general degenerative model (Ma), the remaining data 20 percent is used to test the modal. The hypothesis given by the author is that a network that has been trained with degraded images learns more features and is capable of handling scenarios that are more complicated. Therefore, the model with degraded training sets exhibits better generalization ability.

In this research (Datar et al. 2018) used a dataset that consists of 325 and 275 images provided by the NCVPRIG (BROID) conference. YOLOv2, YOLOv3, and Mask R-CNN are some of the deep learning methods used by the author for bird detection and localizing the birds in the images with clear sky or images where it is hard to distinguish between rocks and birds to the overlapping of birds-to-birds and their reflection from the water bodies. A total of 325 training images are split into 80 percent (260 Images) training set and 20 percent (65 Images) where they use the pre-trained models on the VOC 2012 and COCO dataset, with bounding box coordinates of the birds in the image. 275 test images are used to test all three models by creating a confusion matrix. The F-Scores of 0.8140, 0.8721, 0.8688 for the YOLOv2, YOLOv3 and Mask R-CNN respectively showing YOLOv3 outperforms and Mask R-CNN only marginally lagged behind YOLOv3.

3 Research Methodology

Model Wind energy is the name for the power produced by the wind. As the need for renewable energy sources grows, the government is promoting the use of wind energy, thus wind turbines are operated continuously throughout the day to create the energy to meet the energy supply demand. This study concentrated on the peak hours of the day when wind energy is high so the wind turbines can produce the most electricity in less time. So the wind turbine can operate at the time when there is more wind energy. This will have three benefits at the same time.

a It will produce wind energy which is required by the wind gird to meet the electricity supply-demand

b It will have less maintenance because instead of running the wind turbine throughout the day it will be run during peak hours and the rest of the time it will be shut down.

c When the wind turbine is not operating it will have less effect on natural habitats like birds.

During peak hours when the wind turbine will be operating at that time if there is any bird flying near the wind turbine, the wind turbine will slow down which will help birds to pass through without hitting the turbine blades which will save our natural habitat and especially the birds which are endangered species. All this will be archived by using YOLO which will take images of the flying birds with the help of a camera installed near the wind turbine and give the command to the wind grid to slow down the wind turbine blades so that the birds can pass through the wind turbine blades without hitting then this will save birds.

For this data set, the library which is used are math, NumPy, matplotlib, and pandas. This program is run on google Collaboratory. The historical one-year hourly data is taken from the National renewal energy laboratory (NREL) Texas wind – Turbine for analysis of wind energy prediction which is perfect data and it does not have noisy data. As a result of the dataset, a variety of weather features can be examined and used to predict future weather conditions as shown in figure 1. The data entity used in the data set are :

- Time Stamp
- Pressure (atm)
- Wind Direction (deg)
- Wind Speed (m/s)
- Air Temperature (C)
- System Power Generated (KW)

Time stamp	System power generated | (kW)	Wind speed | (m/s)	Wind direction | (deg)	Pressure | (atm)	Air temperature | ('C)
Jan 1, 12:00 am	1766.64	9.926	128	1.000480	18.263
Jan 1, 01:00 am	1433.83	9.273	135	0.999790	18.363
Jan 1, 02:00 am	1167.23	8.660	142	0.999592	18.663
Jan 1, 03:00 am	1524.59	9.461	148	0.998309	18.763
Jan 1, 04:00 am	1384.28	9.184	150	0.998507	18.963

Figure 1: Dataset table

Dataset Description of Fying birds: The Kaggle dataset, which includes —— images, is used for bird detection. The ratio of 80/10/10 is used to divide these images into train test and validation.

3.1 Learning Model Detail

Due to the unpredictable high rate of change in wind speed within the same length of time with no usual patterns, accurate wind forecasting is the most difficult task. This is because wind speed does not follow a consistent pattern because it depends on various factors like temperature, altitude, and atmospheric pressure. Any machine learning model will find it challenging to identify the ideal pattern and provide correct results. As a time series forecasting problem, wind energy does not follow a consistent pattern over the course of a few hours or days. in order to accurately predict wind speed The most effective machine learning model for time series data prediction is utilized, LSTM. The LSTM will learn the direction of the wind and predict it for electricity generation. will examine the model closely and put it into practice as promptly as possible. This prevention issue is broken down into two parts: - estimation: Here, the dataset columns for temperature, humidity, and pressure are used to predict the wind energy power. Forecast: This power generation pattern is observed during a specific time period, and on the basis of that data, wind energy is forecast independent of weather conditions.

3.2 Prediction

Pure time series analysis is being used. This prediction is done without any prior knowledge about weather power. This is crucial because predicting the weather in the future is a unique machine-learning problem with unique difficulties. Without having access to weather and wind data, electricity generation forecasts are made. LSTM will be used to provide power prediction based on prior patterns. The time stamp and system power generation in the format requested by the LSTM will serve as the data for this forecast. The LSTM will analyze historical data and compile all relevant data regarding the pattern in historical data. It will be possible to forecast power using all of this information. After the LSTM is run on the baseline, 3 distinct models are created to obtain a better look back and other appropriate model parameters.

3.3 Estimation

The generation of wind power based on wind direction is what we are estimating. With the help of temperature and current wind from the dataset, which makes think easier for the LSTM model to compare the current state of the weather with the previous data, that would help to know how much power will be generated by the system. Multivariable time series prediction is used with LSTM with the help of the Keras library. When the baseline model is created and experimentation is done, Eight epochs is a nice quantity for the forecast to yield meaningful results. If the weather information of the present day is given it will be very useful for the estimations models. The best power generation model for the system may then be predicted using this model.

3.4 LSTM

In sequence prediction hourly data, LSTM can learn order dependence from the RNN. The output of the prior data is used as the input for the subsequent data in RNN. LSTM overcomes RNN inability to predict data stored in long-term memory as the gap duration rises. By design, LSTMs can store information for a long time and are frequently used for time series data processing for making predictions and classifying data based on hourly data. LSTM can handle complete data.

3.4.1 Employed Model 1

Data is read from the drive which is in CSV format and the index column is a Timestamp. Normalizing the data. Cleaning of data is performed null values are removed and replaced the null value by *fillna()* function.

To normalize the data from the left skew and right skew log function is used. The values for the power generation have a very high range and low range values, to normalize this *log()* transformation function is used to get a normal range of values. It is a mathematical function that determines the natural logarithm of an input array value, x. Since the natural logarithm log is the inverse of *exp()*, *log(exp(y))=y*. To see how the model is performed on the dataset train test split is used with 70 rows for the train data and 30 rows for the test.

The look-back function is used to create a time frame. Look back is defined as the number of previous time steps used to forecast the upcoming time steps. Using a one-step prediction model, this approach is used. For this model, the *lookback()* period is set to be 8. which means that using the time steps at t-7,t-6,t-5,t-4,t-3,t-2,t-1, and t are used to predict the value of t+1. For the experiment *lookback()*, 6 and 10 are also applied while testing the model but 8 *lookback()* gives the best predictive performance. *stepwise()* movement is used to find the *lookbacl()* eight-time steps before the prediction of the next value. For example, if the value is 6124 train test at time t. in the second entity the value will now move back to time t-1.

3.4.2 Structure of LSTM

The sequential model is used for a stack of layers. To know the model input shape *sequential()* model is used for only the first rest can automatically shape. Eight neuron layers are created for this LSTM model.*model.compile()* (Mean absolute error) MAE or Ll loss. It is occasionally used as an alternative to (Mean squared error) MSE when data collection contains a large number of outliers. It is the average difference between the actual and predicted value.

$$MAE = \frac{1}{m}\sum_{i=1}^{m}(x^i - y^i)^2 \tag{3}$$

where x^i and y^i represent the actual and the predicted values. Adam optimization – Adam is a gradient descent optimization approach. It works well when there is a lot of data and a big problem. Adam is still quite effective while using less RAM. It combines the RMSP algorithm and the gradient descent with momentum algorithms.

After this, the model is trained for 10 epoch and 10 batch size because it gives the best result at this value and take less time, and prevents overfitting of the model. Prediction of the model is printed

The dense layer is used for deep connection with its previous layer which means every neuron is connected with a dense layer with each other. When the return *sequence()* is true dense layer will be applied at every timestep but when it is false it will be applied only to the last cell.

3.4.3 Employed Model 2

Epoch refers to the process of passing a complete dataset through an algorithm during training. supervised learning is used to train algorithms that correctly predict outcomes. Data is input into the supervised model it trains the data and fits the data into the model to give a correct output, it takes the model to learn and train better over time. The *loss()* function is used to measure its accuracy and work until the error is solved. The *lag* function is used to shift the value forward one or more time steps, in this lag value is one, the target value of the next variable will be its last value which is used in the row. For example, if the last value is 1 the lag value will be 1 plus 1 which is 2. The *frame.shift()* function is used to move the index by the required number period with the choice of time-frequency. This function accepts period as the scaler argument, which indicates how many shifts have been made over the desired axis. The *append()* function is used to add rows from another data frame to the end of the current data frame, Concatenate function is used for row-wise data to concatenate data frames and series. *fillna()* method is used to swap out any provided values for any null values. It will give a new data frame because the parameter value is set to true.

Data from time series are transformed via differencing. The series that depend on time can be removed from temporary dependency. Interval one is taken in this model so the system power generation from the first row will be subtracted from the second row. Basically, it is used to subtract the present from the previous value. The element is added to the old list as opposed to the new list. which will add one to the list's length.

The first value of the original series plus the first difference is added together to form inverse differencing.

The inverse transform is used for historical data, *yhat* will take the last value of the prediction and add 1 to it.

The *scaler()* function is used to minimize and maximize the value and the formula for min-max is $x1 = \frac{x-min}{max-min}$ the first minimum is subtracted from the column and then divide by the maximum minus minimum. Transform and update *xtrain* will store the new data of *scaler()* fit transform which is performed on *Xtrain*. In *Xtest* we will be going to scale. transform to update our *Xtest* we won't be fitting our *Xtest*. reshaping of train and test is done which will convert the 2-d *Numpy* array to a 1-d dimension array.

3.4.4 Employed Model 3

we need to re-structure the data with a set of input and output variables, so a time series dataset is used. The lag period is set to be 1 hour so the quantity values are lag by 1 hour. We will be rolling 2 hours on average with a lag of 1 hour to avoid leaking data.

Differencing is done to transform the time series dataset, the series which is dependent on time can be removed by differencing. By subtracting the prior data from the present observation, differentiation is obtained. Difference(t) = observation(t)-observation(t-1). Invert difference is the sum of the original series' first value and its first difference. There is a minute difference due to rounding between the original series and the inverse difference.

When the return sequence is true LSTM layer is followed by a dense layer, and the dense layer is applied for 50 batch size at the final time step when the return sequence is false. Batch normalization is used to make neural networks stable and faster by adding an extra layer. (rectified linear activation function) *relu()* it will output the input function directly if it is true, else it will return zero. *tanh()* is used for a hidden layer activation function real value is taken as an input and output value in the range of -1 to 1. If the value is large output will be positive and if is small output will be negative. One-step forecasting is used to deal with model construction flaws.

3.4.5 Employed Model 4

This model was developed to forecast data for 720 hours. This model has the same methodology as used in model 3.

3.5 YOLO Data Preparation

After dividing the data, the first step in this process is to label the bird dataset using the YOLO labeling tool. Labels are made manually and takes six hours to complete. After labels are created, a *yaml* file is created which contains images with the paths to the train and test. YOLO v5 is used for this research which is an advanced object identification algorithm. It is a CNN that accurately and instantly detects objects. It processes the entire picture using a single neural network, After that, the image is divided into sections, and boundary box predictions are made. The expected probability is compared to predicted boundary boxes. This method just looks at the image once, and when a prediction is formed, a neural network is used. YOLO consists of a three-layer backbone, neck, and head. To extract the important feature from the image, a Backbone is employed. (Cross-stage partial networks) CSP is used as the YOLO backbone for a clear image. When it comes to object scaling, the neck is used to build pyramids. when recognizing the same object in different dimensions. (Path aggregation network) *PANet()* is used as a neck in YOLO v5. Head is used for final detection which uses anchor boxes for the final output. object localization

4 Implementation

In model 1 data is divided into test and train with 70 and 30. After it *lookback()* function is applied in which 8 look back of previous values are seen in it *look-back()* of *trainX()*is 6124 and *testX()* is 2620. In this model reshaping of data is done according to the model requirement then the model is fitted for LSTM deep learning. In it we apply 10 LSTM layers with 1 dense layer, loss *mae()* is used with *adam()* optimizer and it is run on 10 epochs with a batch size of 10. The prediction model is performed. The First 500 entries are used for prediction and prediction is shown in the blue line in pyplot and the truth is shown in orange the result which comes out in pyplot is approx equal to the prediction = true which means that our model is good for train and test.

In model 2 hardcodes of the variable are done with a batch size is 1 which is run on 7 epochs with 10 neural layers and a lag value is 24. The data framing is done with a lag value of 1 concatenation is done on the data frame and all the true values are filled with 0 with *fillna()* function. Different series of data is created in which the interval value is 1 which means 1 will be minus from the previous data. Then invert differencing is performed with *yhat()*. *MinMax sclaer* is used for fitting the value, and transforming train and test data is done with scaler transformation. Inverse scaling is done for forecasting the value. LSTM is applied to the data with a dense layer of 1 and the data is compiled by applying mean squared error and *adam* optimizer is used and it is run on 1 epoch. All the values are dropped except the time stamp and system power generated so check the prediction value. One-step forecasting is done by replacing the test value with the predicted value, and invert scaling and invert differencing are done.

Model 3 hardcode predicted batch size is 1 which is run on 50 epochs with a neuron layer of 5 and it is run for 1 weak of data with a lag value of 24. Data framing is done with a lag value of 1, filling all the missing values using *fillna()* function. *yhat* is used for invert differencing, scaling the train and test data with min-max scaler and the range is -1 to 1. Transforming is done on train and test data by reshaping it, LSTM layer is applied with Keras layer batch normalization is added with dense layer '*relu()* and *tanh()* function is used. Compile is done on mean squared error an *adam* optimizer is used. One-step forecasting is done with a batch size of 1.

Model 4 window size is taken 24 which is run on 10 epochs with a neuron layer of 50 and its runs on a prediction of 1 month. Time series are used for supervision with a lag of 1, concatenation is done on data set columns null values are filled with 0. Scaling of train and test is done with MinMax scaler within a range of -1 to 1. Data transformation is done on the train. LSTM is applied to training data with the Keras library using batch normalization with a dense layer of 50, and activation functions *relu()* and *tanh()* are used. Loss means square error and *adam* optimizer is used for the compiler. Replacing the test value with the predicted value using *yhat*, invert scaling, and differencing are used.

Flying Bird YOLOv5 pretrained model is used to create this model. Pretrained model is cloned from the github from below link.[1]

YOLOv5s model is used as pretrained weights for birds detection. Initially the train data is run with default configuration of YOLO which is epoch size 10, Batch size 8 and image size 640. To increase the accuracy later epoch size is changed to 25 and 25 to 50. With this configuration accuracy was good.

Lastly *detect.py* file is used to test the images with on the train model weights.

5 Evaluation

All the plots are shown below. The predicted hours are represented by the X-axis and The power produced by the system is shown on the Y-axis. The graph shows an orange line for expected power generation and a blue line for actual power generation.

5.1 Model 1

one year hourly date is divided into 70-30 train test batches for this model, first 500 entities are used for evaluating the optimal hour's prediction and it gives out perfect prediction as shown in figure 2 for the prediction and true value. The MSE of the model is 0.095 and the (Root mean squared error) RMSE of the model is 0.308 which is very good for this experiment

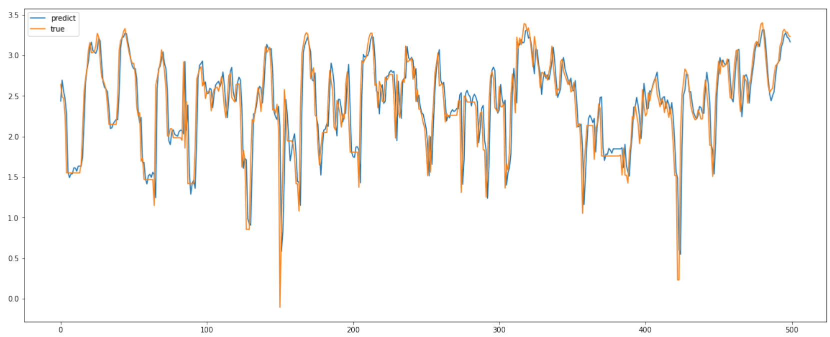

Figure 2: Prediction based on the first 500 entries in the plot

[1]https://github.com/developer0hye/Yolo$_{L}abel/releases/download/v1.1.1/YoloLabel_{v}1.1.1.zip$

5.2 Model 2

The same model configurations were used to forecast data for 24 hours. The power generated by the system (KW) is represented by the Y-axis and The number of hours used by the system is shown on the X-axis. For this model, the mean absolute percent error is 52.52 percent. This is a good prediction for one day ahead which can be seen clearly in Figure3. LSTM is able to find the true data which is expected to be the predicted data The LSTM parameters for this model are the input value for the batch size is 1 and it is run on 7 epochs with 10 layers of neurons and look back or lag for 24.

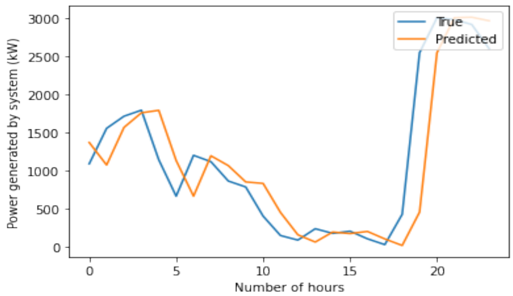

Figure 3: Line graph of observed vs predicted for 24 hours

5.3 Model 3

Data were predicted for 168 hours using the same model setups. the LSTM parameters for this model are batch size 1 which is run 0n 50 epoch with 5 layers of neurons and having a look back of 24. the mean absolute percent error comes out to be 59.76 percent. Figure 4

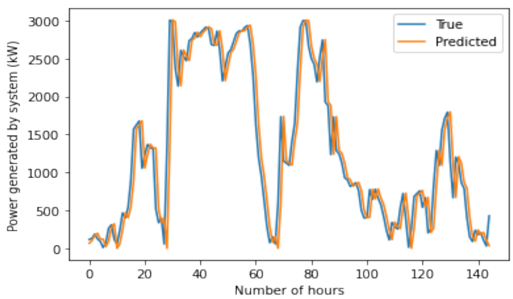

Figure 4: Line graph of observed vs predicted for 168 hours

5.4 Model 4

The same model sets are used for 720 hours of data prediction. LSTM parameters window size is 24 with a batch size of 1 which is run on 10 epochs with 50 neuron layers at 24 look-back value. It turns out that the mean absolute percent inaccuracy is 69.20 percent and graph can be seen in figure 5

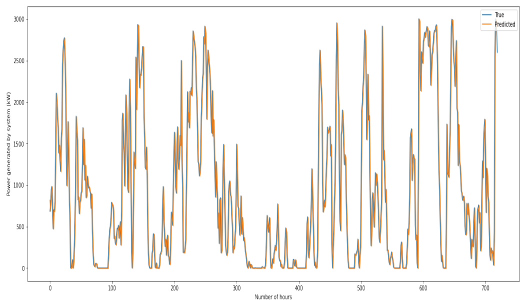

Figure 5: Line graph of observed vs predicted for 720 hours

5.4.1 Evaluation of YOLO bird model

By using above figure 6 we can clearly see that our model is able to detect the bird species. The model is run for 50 epochs box loss start getting less value after 25 epoch which is below 0.03. In metrics precision value is above 95 after 10 epochs. The value of *mAP* is 96 percent after 10 epoch are run this shows that this model has high accuracy.

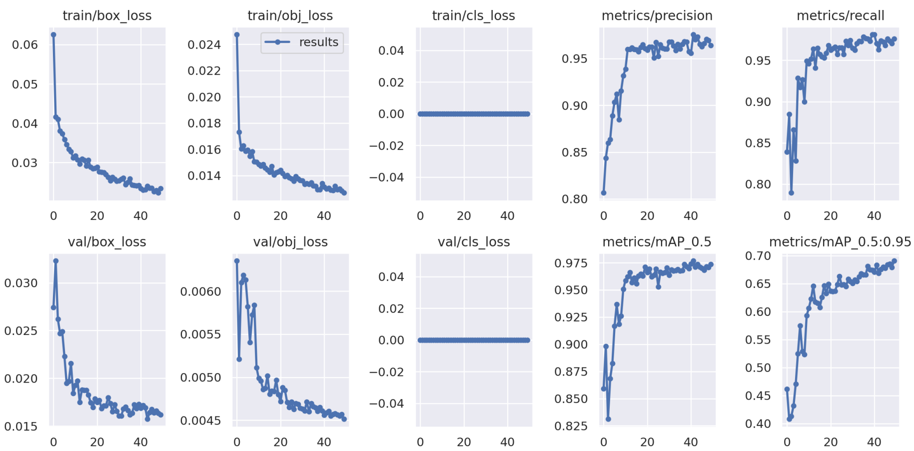

Figure 6: Precision recall graph chart

Figure 7: Bird detection by YOLO

In the given figure 7 we can clearly see YOLO model able to detect the flying birds.

6 Combining two model

working of two different models in figure 8 is shown. when wind turbines are operational and if there is any bird flying towards the wind turbine blades, a 360-degree camera is installed on the wind turbine which will capture the image of the flying bird and then pass that image to the YOLO v5 model which is made in this project, YOLO will do the image processing and if the flying object is detected as the bird it will send command to the wind turbine controller to slow down the wind turbine. that will give time for the birds to pass through the wind turbine blades without hitting the turbine blades which will save numerous amount of bird life. the wind turbine still be operating at a slow speed and generate power. so at the same time, we are generating electric power and saving the bird's life.

7 Conclusions and Future work

In this project wind energy prediction will help wind mills grid to get accurate wind energy generation data for each hour which will help the grid to meet wind energy supply demand. The aim of this project is to have less on the other side, it will save numerous bird's life. The data utilized in this research is outdated and

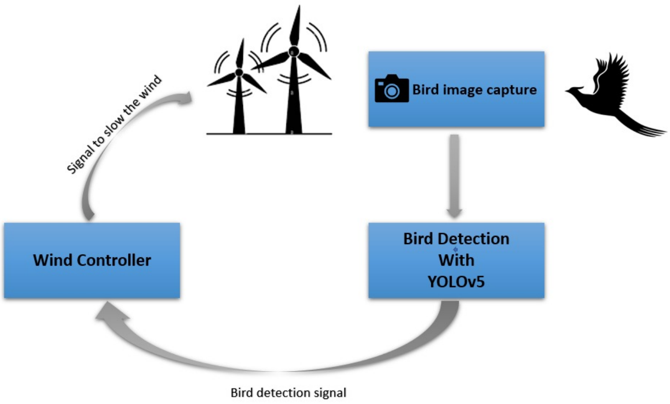

Figure 8: wind turbine and bird detection

contains fewer than 8760 entities, which is insufficient for accurate prediction. The large and new dataset will be taken for future analysis which will help to give accurate forecasting. For bird detection instead of using images, live video will be used for detecting birds which will take less processing time with the latest version of YOLO.

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