A Dynamic Pricing System For E-Scooter Based On Demand Prediction Using Neural Network

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Abstract

Due To The Rise Of Pollution In Our Environment, There Is An Increase In The Demand For Recyclable Vehicles, Which Help In Controlling Pollution. To Make The Environment Pollution-Free And To Provide A Convenient Mode Of Transport To The People, We Have Introduced A Suitable Method For Usage Of E-Scooters. The Demand For E-Scooters At Each Dock On Different Day's And Time Is Predicted Using Neural Networking And Managed Using A Dynamic Pricing System. With The Help Of Dynamic Pricing, The Supply Of E-Scooters At Each Dock Can Be Well Managed By Charging The Price Of E-Scooters According To Its Requirement. The Proposed System Concentrates On The Advanced Prediction Of The Demand Over The E-Scooters Using Which Pricing Is Done Dynamically. Since The Spatio-Temporal And Other External Factors Influence The Usage Of E-Scooter In Each Geographical Location. The Neural Network Is Used To Gain Sufficient Information From The Pre-Existing Data Set. As A Result, The Demand For The E-Scooters At Each Location Is Predicted Hence The Pricing Can Be Done Dynamically.

***Keyword** – Dynamic Pricing, E-Scooter, Neural Network, Prediction, Spatio-Temporal*

1. Introduction

Over The Globe Today, Climate Change Being A Buzzword. The Adequate Measure Taken Into Action Starts From The Whole Lot. While The Top Industrious Cities Are Being Environmentally Sound, Electronic Scooters Are Becoming Habitual. There Are Many Common Problems Faced Because The Use Of E-Scooters Is High Around The Region, Such As The Demand Forecast And Their Dynamic Or Search Pricing, Taking Into Account Different Factors Such As Weather, Festivals, Peak Hours, Working Days, Holidays, And Many More. In This Manner, The Precise Expectation For How Many E-Scooters Are To Be Rented And Returned All Through The City And Their Registered Or Unregistered User Is Important, In Light Of Which E-Scooter Pricing Can Be Directed Ahead Of Time, For Example Increasing E-Scooters Price During Engrossed Days And Curb The Price When They Are Idle. The Significant Objective To Be Accomplished Here Is Predicting The Count Of Registered And Unregistered E-Scooters Users Over Time, Utilizing The Previous Informational Index That Comprises The Check-In, Check-Out Information, Rent And Returns Information, And Several Other Spatio-Temporal Information, And Then Dynamically Pricing The E-Scooters.

Due To The Swift Development Of The Shared Economy, Sharing E-Scooter Has Become One Of The Most Favoured And Suited Mode Of Traveling In Intelligent Transport Systems. Aiming To Improvise Cost Policies. The Operators Of E-Scooter Sharing Systems Need To Dynamically Price The E-Scooters. Predicting The Number Of E-Scooter For Each Dock Can Help To Optimize The Demand Prediction And Pricing Of Them. The Usage Of E-Scooter Is Affected By Several Undetermined Factors, So The Number Prediction Becomes A Challenging. Hence This System Plays A Vital Role In Training The Neural Network With Previous Data That Consists Of Features And Targets. During The Course Of Multiple Training, The System Imbibes The Pattern And Tends To Predict The Existent Registered, Unregistered, And Total Users Of That Day With Which The Pricing Can Happen. That Is The Deduction Of The Price For The Idle System And Increase Of Price For Uplifted Demand. This Way E-Scooter Sharing System Can Be Priced Dynamically Using The Predicted Demand By The Neural Network.

2. Literature Survey

As There Are Major Other Projects The Effective Demand Prediction Is Yet To Be Improved. In [1] The Demand Is Predicted Using The Clustering Algorithm And Pattern Recognition Algorithm With The Help Of Pre-Existing Data. The Demand Is Well Predicted Using The General Last Square Formula. All The Algorithms Are Advanced And The Demand Is Predicted Accurately. However, The Pricing Of The E-Scooters Is Not Mentioned In Detail. In [2] For Increasing The Travel Efficiency For Users The Mobile

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System Is Used For Bike-Sharing Using Mysql And Java, This Paper Mainly Focuses On Boosting The Number Of The Bike-Sharing System Using Various Methodologies Such As Login Module, Lessee Module, Lessor, And Administration Modules. The Main Benefit Is To Reduce The Traffic And Reducing The Pollution. The Major Issue In The Paper Is The Irregular Allotment Of Bikes At Each Dock. The Disadvantage Is The Usage Of Mobile Applications Which Is Not A User-Friendly Approach. In [3] The Paper Mainly Focuses On Creating A Station Less Bike-Sharing System, Where The Bike Can Be Rented And Returned At Any Place Using The Mobile Application. The Drawback Of The Paper Is That The Bikes Are Returned At Random Places By The Previous Users, The Next User Might Find It Difficult To Locate The Bike. In [4] It Mainly Focuses On Central Stations, The Station Where There The Bike Demand Is High When Compared To Other Station. It Focuses On Filling The Required Amount Bike In The Central Stations First And The Remaining Bikes Are Distributed To Stations. The Drawback Of The Paper Is That It Focuses Only On Central Stations. In [5] Mobility Modelling Algorithm Is Used To Solve The Uneven Distribution Of Bikes. The Drawback Is That The Mobility Module Has To Be Updated In This System. In [6] This Paper Focuses On Both The Station And The Station Less Bike-Sharing System To Make It More Convenient To The Users So That The User Can Rent And Return From The Dock To Dock Or Can Rent From A Random Place And Return At A Convenient Place. In [7] The Prediction Is Done By Using A Rebalancing Module And Machine-Learning. This System Also Concentrates On The Dock-Based And Station-Less Systems. It Becomes Hard In Recovering Bikes In The Case Of Station Less System Which Acts As A Major Drawback.

3. Existing System

The Existing System Focuses On The Efficient Operation Of The Bike-Sharing System. The Bike Usage Is Predicted Using A Hierarchical Consistency Prediction Model. The Clustering Algorithm And Pattern Recognition Algorithm Are Used To Gain Sufficient Information From The Pre-Existing Data Set. As A Result, The Demand Over The Rent And Return Of Bikes At Each Dock Is Predicted Hence The Demand Can Be Met Easily. The System Is Designed In A Way Where A Person Can Rent Or Return The Bike At An Arbitrary Dock Through A Membership Account Or Card. The Stations Are Huddled Into Groups Using The Clustering Algorithm. To Foretell The Count Of Bikes That Are Rented At Each Dock The Similarity-Based Efficient Gaussian Process Regressor Is Used. Finally, The Ultimate Predictions For The Rent Of Bikes Are Made More Practical With The Help Of The General Least-Square Formula.

4. Proposed Methodology

The Proposed System Mainly Focuses On The Dynamic Pricing Of The E-Scooters Like Raising The Price Of E-Scooters When They Are In Excessive Demand And Reducing The Rent Price When There Is Less Demand. Increasing And Decreasing The Price Of E-Scooters Also Depends On Various Factors Taking Into Consideration Of Weekdays, Weekends, Festivals, Holidays Etc.

The Demand For E-Scooters Is Predicted Using The Neural Network With The Help Of The Previous Data Set. The Neural Network Is Given The Input Of The Previous Data Set And Is Trained Multiple Times To Give An Accurate Demand For The E-Scooters Based On All Factors, And The Pricing Is Done Based On Their Demand. Each Time The Demand Needs To Be Predicted The Input Is Given To The Neural Network And The Output Matrix Is Obtained And The Number Of E-Scooters Required Can Be Predicted For Total Users Which Include Registered Users And Casual Users, And The Price Of The E-Scooters Can Be Pitched According To Its Demand. For Example, If The Prediction Is Required For Sunday And The Input Is Given As Sunday In The Neural Network It Calculates The Average Number Of E-Scooters That Have Been Rented And Returned On All Sundays From The Previous Data Set That Has Been Updated In The Neural Network And The Price Is Increased If The Demand Is High Or It Is Decreased When The Demand Of E-Scooters Are Less.

5. System Architecture

This System Provides A Technique For Efficient Prediction Of Demand, The Neural Network Is Used To Train The System Multiple Times With The Pre-Existing Dataset. The Dynamic Pricing System Is Generated As Shown In Figure.

Figure. 1: System Architecture

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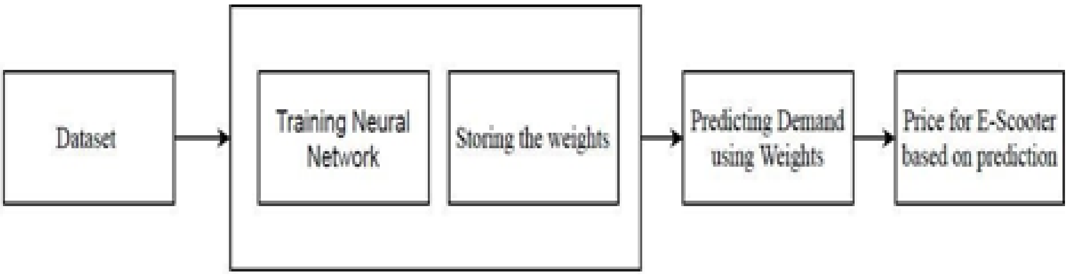

5.1. Dataset

These Are The Pre-Existing Data Of A Year Which Consists Of Two Vivisections. One Is The Features And The Other Is The Target. The Features Consist Of The Spatio-Temporal Data's Such As Date, Season, The Year, The Month, Hour Of The Day, Holidays, Weekdays, Weather, Temperature, Atmospheric Temperature, Humidity, Wind Speed, Etc. And The Target Consists Of The Number Of Registered Users, Casual Users, And Total Users In That Particular Day. Here The Features Act As A Condition While Training The System And The Target Input Helps In Achieving The Target Output Of Registered, Casual, And Total Users. When The Current Day's Demand Has To Be Predicted, The System Tends To Use The Learning From The Features And The Previous Target To Predict The Current Demand Of The Day.

5.2. Training Neural Network

The Neural Network Consists Of 3 Layers. The Input Layer, The Hidden Node Layer, And The Output Layer. The Input Layer Consists Of Each Day Of A Year As Multiple Rows Having Features And Targets As The Column. In The Hidden Layer, Multiple Hidden Nodes Are Present Which Was Extracted From The Learning Of Multiple Pieces Of Training Done To The System. They Obtain A Trained Weight That Consists Of A Random Matrix. And The Output Layer Provides The Target Output Consisting Of The Registered, Casual, And Total Users.

5.3. Storing Weights

Trained Weights Are Stored In The Hidden Layer At Multiple Nodes. The Iterations Of Learning Frame A Random Column Matrix That Is Used To Obtain The Target Output. These Hidden Layers, Nodes, And Weights Play A Vital Role In A Neural Network.

5.4. Predicting Demand Using Weights

The Output From The Neural Network Provides The Number Of Registered Users, Casual Users, And Total Users. The Trained System Tends To Predict The Demand Of E-Scooters On That Particular Date Based On The Trained Weights Gained From Features And Targets Iterated Learning. These User Definitions Are Used In Pricing The E-Scooter Depending On The Higher Or Lower Demand And The User Being Registered Or Walk-In.

5.5. Pricing E-Scooter Based On Demand Predicted

Dynamic Pricing Of The System Is Done By Taking The Mean Of The Total Users Predicted By The Neural Network. If The Predicted Users Are Less Than The Mean Of Total Users Then The Price Is The Optimal Price Minus The Segregate Of Optimal Price, Predicter Total Users, And The Mean Of The Total User. This Price Is Later Taken Product According To The User Being Registered Or Walking. This Dynamic Pricing Using The Predicted Demand From Neural Networks Helps In Business Development And Helps The System Economically.

6. Modules

For A Sound Prediction Of Demand From Pre-Existing Datasets, There Is A Requirement For A Resourceful And Sensible Approach Towards What Methods To Be Used. The Neural Network Is A Progression Of Calculations That Tries To Perceive Basic Connections And Patterns In A Bunch Of Data Through A Cycle That Mirrors How The Human Mind Works. With The Assistance Of A Prior Informational Collection That Contains The User Data And Other Spatiotemporal Qualities, The System Is Trained On Different Occasions To Predict The Current Demand Utilizing Which The E-Scooter Sharing System Can Be Dynamically Valued.

6.1. Neural Network

Figure. 2: Neural Network Architecture

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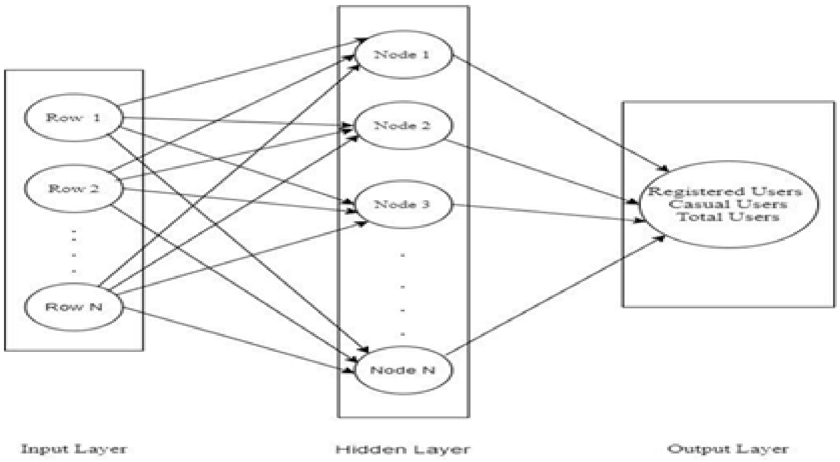
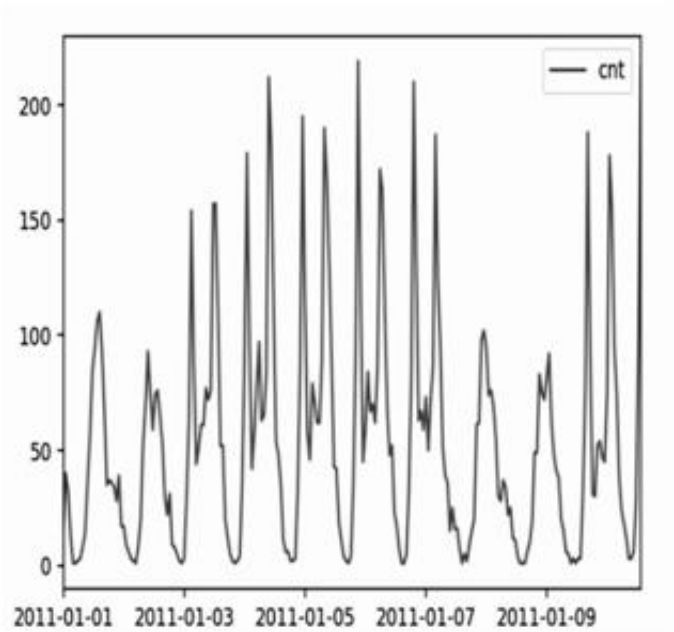


The System Has 3 Layers, An Input Layer, A Hidden Layer, And An Output Layer. The Hidden Layer Will Utilize The Sigmoid Capacity For Initiations. The Output Layer Has Just A Single Node And Is Utilized For The Relapse, The Output Of The Node Is Equivalent To The Contribution Of The Node. The Work Through Each Layer Of The Organization Computes The Output For Every Neuron. The Entirety Of The Output From One Layer Becomes Contributions To The Neurons On The Following Layer. The Weights Are Utilized To Proliferate Flags Forward From The Contribution To The Output Layers In A Neural Organization.

6.2. Pre-Existing Data

This Dataset Has The Number Of Users For Every Hour Of Every Day For A Year. The Quantity Of Riders Is Part Of Registered And Casual, Summarized In The Cnt Segment. The Following Is A Plot Showing The Quantity Of E-Scooter Users Over The Initial Days Or So In The Informational Collection. The Hourly Rentals Can Be Seen. The Ends Of The Week Have Lower Overall E- Scooter Users And There Are Spikes When Individuals Are Riding To And From Work During The Week.

Figure. 3: Pre-Existing Data Graph



6.3. Learning Rate

This Scales The Size Of Weight Updates. On The Off Chance That This Is Too Enormous, The Loads Will In General Detonate And The Network Neglects To Fit The Information. The Lower The Learning Rate, The More Modest The Means Are In The Weight Updates And The More It Takes For The Neural Network To Unite. The Number Of Clumps Of Tests From The Training Data Will Be Utilized To Prepare The Network. The More Iterations Utilized, The Better The Model Fits The Information. Be That As It May, This Interaction Can Have Pointedly Unavoidable Losses And Can Squander Computational Assets Whenever

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Utilized An Excessive Number Of Emphases. A Number Ought To Be Found Here Where The Network Has A Low Training Loss, And The Validation Loss Is At Least. The Ideal Number Of Cycles Would Be A Level That Stops Soon After The Validation Loss Is Done Diminishing.

6.4. Hidden Nodes

In A Model Where All The Weights Are Improved, The More Hidden Nodes Present, The More Exact The Forecasts Of The Model Occur. Notwithstanding, The More Hidden Nodes, The Harder It Will Enhance The Weights Of The Model, And The More Probable Imperfect Weight Will Prompt Overfitting.

With Overfitting, The Model May Remember The Preparation Information As Opposed To Learning The Genuine Example, And Will Not Sum Up Well To Concealed Information. If The Quantity Of Covered-Up Units Is Too Low, The Model Probably Won't Have Sufficient Space To Learn, And If It Is Excessively High There Are Such A Large Number Of Alternatives For The Bearing That The Learning Can Take.

6.5. Stochastic Gradient Decent

The Methodology Here Is To Discover Hyperparameters To Such An Extent That The Mistake On The Preparation Set Is Low, Yet Not Overfitting To The Information. On The Off Chance That The Network Is Prepared Excessively Long Or Has Too Many Hidden Nodes, It Can Turn Out To Be Excessively Explicit To The Preparation Set And Will Neglect To Sum Up To The Training Set. That Is, The Misfortune On The Training Set Will Begin Expanding As The Preparation Set Misfortune Drops. The Technique Known As Stochastic Gradient Descent Is Utilized To Prepare The Network. The Thought Is That For Each Training Pass, An Irregular Example Of The Information Is Taken As Opposed To Utilizing The Entire Informational Collection. Here A Lot More Training Passes Are Utilized Than With Typical Inclination Plunge, Yet Each Pass Is A Lot Quicker. This Winds Up Preparing The Organization All The More Productively.

6.6. Demand Prediction

The Predicted Demand Exhibits The Registered, Casual And Total Users, Which Corresponds To The Dynamic Pricing Of An E-Scooter Sharing System. The Output Graph Almost The Same As The Data Graph Thus Proving The Efficiency Of The Neural Network.

6.7. Dynamic Pricing Based On Demand Predicted

$$meantc = \sum_{k=0}^{n} tck$$

$Price = optimalPrice$

$if\ meantc - predictedtc < 50\ and\ meantc > predictedtc:$

$$Price = Price - \left[\frac{Price * meantc - predictedtc}{meantc} \right]$$

$if\ predictedtc - meantc > 50\ and\ predictedtc > meantc:$

$$Price = Price + \left[\frac{Price * predictedtc - meantc}{meantc} \right]$$

$if\ day\ in\ weekends\ or\ holidays:$

$registeredUserprice = Price - (Price * 0.2)$

$unregisteredUserprice = Price - (Price * 0.1)$

$tck = Total\ count\ of\ users\ per\ day\ in\ the\ dataset$

$n = Total\ number\ of\ rows\ in\ the\ dataset$

$meantc = The\ mean\ of\ total\ count\ in\ the\ dataset$

$predictedtc = Total\ number\ of\ predicted\ users$

Table. 1: Pre-Existing Dataset

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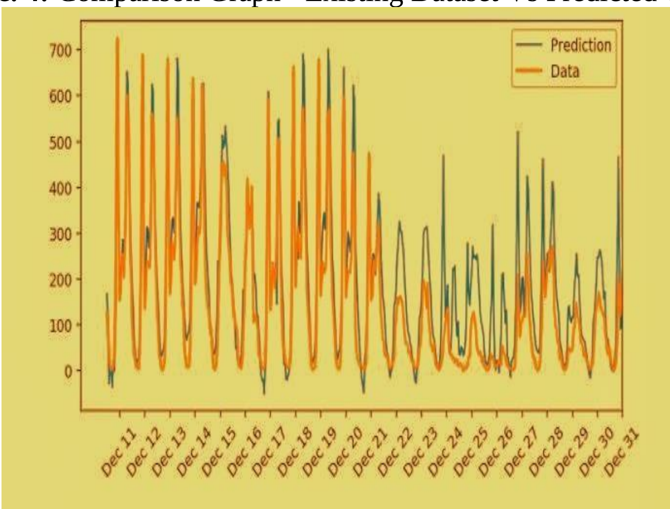
	year	holiday	temperature	humidity	windspeed	casual	registered	total_count	season_1	season_2	...	hour_21	hour_22	hour_23	weekday_0	we
0	0	0	0.24	0.81	0.0000	3	13	16	1	0	...	0	0	0	0	
1	0	0	0.22	0.80	0.0000	8	32	40	1	0	...	0	0	0	0	
2	0	0	0.22	0.80	0.0000	5	27	32	1	0	...	0	0	0	0	
3	0	0	0.24	0.75	0.0000	3	10	13	1	0	...	0	0	0	0	
4	0	0	0.24	0.75	0.0000	0	1	1	1	0	...	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
17374	1	0	0.26	0.60	0.1642	11	108	119	1	0	...	0	0	0	0	
17375	1	0	0.26	0.60	0.1642	8	81	89	1	0	...	0	0	0	0	
17376	1	0	0.26	0.60	0.1642	7	83	90	1	0	...	1	0	0	0	
17377	1	0	0.26	0.56	0.1343	13	48	61	1	0	...	0	1	0	0	
17378	1	0	0.26	0.65	0.1343	12	37	49	1	0	...	0	0	1	0	

17379 rows × 59 columns

7. Experimental Result

In Real-Time, The Predicted Information Of Total Users Is Being Conjugated With The Optimal Price To Achieve The Price. This Price Is Then Aggregated With Their Particular Registered User And Casual User Variant To Provide The Final Dynamic Price For Each Sector Of People. This Way E-Scooter Sharing System Gets Demand Predicted And Their Prices Declared For The Consistent Functionality Of The System.

Figure. 4: Comparison Graph - Existing Dataset Vs Predicted Output



The Graph Shows The Spikes Of The Predicted Data To That Of The Original Data. When Observed The Results Are Most Likely To Predict The Precise Demand. This Prediction Further Takes A Turn By Dynamic Pricing Providing A Business-Friendly And Economical System.

8. Conclusion

The Demand For E-Scooters Is Predicted By The Neural Network Which Has Been Trained Using The Previous Data Set. Using The Dynamic Pricing System, The Demand Of The E- Scooters Can Be Well Handled For The Registered Users And Casual Users By Increasing And Decreasing The Price Of The E-Scooters According To Its Claim.

As The Demand For E-Scooters Is High On Holidays And Weekends The Price Is Increased Accordingly To Reduce The Crowd And To Avoid A Shortage Of E-Scooters At Each Dock. During The Days Where The Demand Is Less The Price Is Decreased To Attract The Crowd And To Avoid Inadequate Use Of E-Scooters.

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