Application of AI-Based Techniques for CNC Machining (Milling)

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Abstract— Tool life prediction is crucial in CNC milling to optimize machining operations and reduce costs. This study explores the application of artificial neural networks (ANNs) for predicting tool life based on machining parameters such as RPM, feed speed, axial depth of cut, and radial depth of cut. A dataset is utilized to train and evaluate the ANN model, which is optimized using standard scaling and Adam optimizer. The results demonstrate the efficacy of ANNs in accurately forecasting tool life, enabling proactive maintenance and enhancing machining efficiency and comparing with MATLAB.

Index Terms- Artificial Neural Networks, CNC Milling, MATLAB

I. INTRODUCTION

Artificial intelligence (AI) is a broad field of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence. In other words, we can say that it aims is to make computers smart and intelligent by giving them the ability to think and learn using computer programs or machines, i.e., can think and function in the same way that people do. From a philosophical perspective, AI has the potential to help people live more meaningful lives without having to work as hard, as well as manage the massive network of interconnected individuals, businesses, states, and nations in a way that benefits everyone. Thus, the primary goal of AI is to enable computers and machines to perform cognitive functions such as problem-solving, decision-making, perception, and comprehension of human communication. Therefore, AI- based modelling is the key to building automated, intelligent and smart systems according to today's needs, which has emerged as the next major technological milestone, influencing the future of practically every business by making every process better, faster, and more precise.[4]

CNC machining operation is one of the most important parts of production methodologies, and it is often referred to as the engine of modern manufacturing in aerospace, gas and oil, and warehousing services, are using the CNC machining operations to create parts in different applications. CNC machining is generally used in the manufacture of every machine, moulded part, or finished product as one of the most important manufacturing processes.[1] CNC machinery has paved the way in manufacturing and machining, allowing businesses to achieve their goals and targets in a variety of ways. However, because manufacturing methodologies are always evolving and new technologies are being introduced, it is critical to consider the future of CNC machining operations. Machine learning (ML) is the study of computer algorithms that gives computers the capacity to automatically learn from data and prior experiences to find patterns and make predictions without human involvement. ML and applications in different areas of study are Machine learning and artificial intelligence in particular raise plenty of concerns about the future of CNC machining operations and how these concepts will evolve future works of manufacturing companies. The way a machine learns adapts and optimizes output can also be intended by real-time data, analytics, and deep learning. Data sets are essential for operators to understand how a machine works and, eventually-ally, how a whole floor of machines works together. Due to the development of affordable, reliable, and resilient sensors and acquisition and communication systems, novel implementations of machine learning approaches for tool condition monitoring can be presented.[14] Machine learning systems are capable of completely examining data and identifying various types of areas which should be modified. Machine tools are increasingly being equipped with edge computing options to record internal drive signals at high frequency to supply the necessary vast quantity of data for the use of machine learning techniques in manufacturing. Productivity and efficiency are two areas where artificial intelligence can modify CNC machine tools operations in order to enhance accuracy of CNC machining operations. Machines can generate and analyze production data and provide real-time findings to human operators are effective devices for increasing productivity in part production processes. As a result, shop owners can quickly adjust the way a machine operates using the modified data generated by advanced machine learning algorithms to enhance productivity of part manufacturing. Having more knowledge and making better decisions in process planning strategies means less downtime on the work floor during the process of part production. [20] The production and maintenance process of part manufacturing using CNC machine tools can be developed using machine learning and artificial intelligence to enhance efficiency in part manufacturing operations. The CNC machining operations must be optimized to save money and time. Artificial intelligence can forecast periods of servicing and equipment of CNC machine tools structures by linking to production data such as machine performance and tool life. [2] Deep learning for smart manufacturing.

Thus, we take into account several AI categories: The first one is "*Analytical AI*" with the capability of extracting insights from data to ultimately produce recommendations and thus contributing to data-driven decision-making; the Second one is "*Functional AI*" which is similar to analytical AI; however, instead of giving recommendations, it takes actions; the Third one is "*Interactive AI*" that typically allows businesses to automate communication without compromising on interactivity like smart personal assistants or chatbots; the Fourth one is "*Textual AI*" that covers textual analytics or natural language processing through which business can enjoy text recognition, speech-to-text conversion, machine translation, and content generation capabilities. Although the area of "artificial intelligence" is huge, we mainly focus on potential techniques towards solving real-world issues, where the results are used to build automated, intelligent, and smart systems in various application areas. To build AI- based models, we classify various AI techniques into ten categories: (1) machine learning; (2) neural networks and deep learning; (3) data mining, knowledge discovery and advanced analytics; (4) rule-based modeling and decision-making; (5) fuzzy logic-based approach; (6) knowledge representation, uncertainty reasoning, and expert system modeling.
(7) case-based reasoning; (8) text mining and natural language processing; (9) visual analytics, computer vision and pattern recognition; (10) hybridization, searching and Optimization. These techniques can play an important role in developing intelligent and smart systems in various *real-world application* areas that include business, finance, healthcare, agriculture, smart cities, cybersecurity, and many more, depending on the nature of the problem and target solution.[12] Thus, it is important to comprehend the concepts of these techniques mentioned above, as well as their relevance in a variety of real-world scenarios.

1.1 Design Calculation:

- Taylor tool life equation relates to the tool life.
  - $\boldsymbol{VT^n}$ = C
  - V= Cutting Speed at which the cutting tool moves through the work material.
  - C= A constant that depends on the tool, work material, and cutting conditions.
  - T= Tool life (usually in minutes)
  - n = Exponent that varies based on tool material and cutting conditions
- Modified version of Taylor's equation,
  - $\boldsymbol{VT^n f^a d^b = Kt}$
  - V = Cutting Speed
  - T = Tool Life
  - f = Feed Rate
  - d = Depth of Cut
  - n, a, b = Exponents that vary based on tool material and cutting conditions

Kt = Tool Life Constant (a factor based on experimental data)

II. METHODOLOGY

2.1 CNC Machining (Milling):

CNC (Computer Numerical Control) milling is a sophisticated machining process used to precisely shape metal, plastic, and other materials into complex parts and components. This automated technology employs computer- controlled machines to perform a variety of cutting operations, including drilling, slotting, and contouring, with high precision and repeatability. CNC milling machines operate using a rotating cutting tool that moves along multiple axes to remove material from a workpiece, guided by a pre-programmed sequence of commands in the form of G-code.

The key advantages of CNC milling include its ability to produce high-quality, intricate parts with tight tolerances, making it ideal for applications in aerospace, automotive, and manufacturing industries. Modern CNC mills are equipped with advanced features such as multiple-axis capabilities, automated tool changers, and real-time monitoring systems, which enhance productivity and operational efficiency. By integrating CAD/CAM (Computer-Aided Design/Computer-Aided Manufacturing) software, CNC milling allows for the efficient translation of design specifications into physical components, significantly reducing production time and costs. As a versatile and reliable manufacturing technology, CNC milling continues to play a crucial role in advancing precision engineering and innovative product development.

Fig 2.1 CNC Face milling


Fig 2.2 Face milling Tool

Spindle Power Fanuc	3.7/ 5.5kW
Spindle Speed	80 - 6000 Rpm
Z - Axis Travel	320 mm
Pallet Size	650 mm x 400 mm
Brand	Ace Micromatic
Machine Width.	1800 mm
Tool Change System.	Disc Armless
Machine Depth.	2800 mm
Machine Height.	2500 mm
CNC-Control	FANUC OMIF
Machine Net Weight	3200 Kgf
Chip-To-Chip Time	2.7 Sec
Number-Of Tools	12
Y Axis Travel	400 mm
X Axis Travel	500 mm
Maximum Load On Table	400 Kgf
Distance From Spindle Face To Table Top	110 - 430 mm
Spindle Nose Taper.	7 / 24 No.30
Guideways	LM
Rapid Traverse X, Y & Z Axes	48 / 48 / 40 (m/min)
T-Slot Diameter	3 (N) x 14 (W) x 125 (P)

Table:1.1 Machine specifications

2.2 Procedure:

2.2.1 Procedure for AI Model in MATLAB

MATLAB:

MATLAB (Matrix Laboratory) is a high-level programming language and interactive environment developed by MathWorks. It is widely used for numerical computing, data analysis, and visualization. MATLAB provides a rich set of tools for mathematical computation, including built-in functions for linear algebra, statistics, optimization, and signal processing.

One of MATLAB’s core strengths is its ability to handle and manipulate matrices, which are fundamental to many scientific and engineering computations. Users can perform complex mathematical calculations, develop algorithms, and model systems using its extensive library of functions and toolboxes.

MATLAB's user-friendly interface includes a command window, workspace, and built-in editor for creating scripts and functions. It also supports advanced data visualization techniques, such as 2D and 3D plotting, which help users interpret and present their data effectively.

Applications of MATLAB span various fields including engineering, physics, finance, and machine learning. It is commonly used for tasks like data analysis, system simulation, control design, and developing machine learning models. MATLAB also integrates with other programming languages and software, enhancing its versatility for complex project development.

1. Load the Dataset

Description: Load your dataset from a CSV file while keeping the original column headers.

2. Display the Data

Description: Show the first few rows of the data to confirm it loaded correctly.

3. Extract Features and Target

Description: Separate the features and target variable from the dataset.

4. Normalize the Features

Description: Normalize the features using min-max normalization to the range [0, 1]

5. Split the Data into Training and Testing Sets

Description: Divide the data into training and testing sets (80% for training, 20% for testing).

6. Create and Train the Neural Network

Description: Define and train a feedforward neural network with 10 neurons in one hidden layer.

7. Make Predictions on Test Data

Description: Use the trained model to predict tool life on the test dataset.

8. Evaluate the Model Performance

Description: Calculate and display the Mean Squared Error (MSE) of the model's predictions.

9. Save the Model and Normalization Parameters

Description: Save the dataset, trained model, and normalization parameters to a .mat file for future use.

10. Load the Model and Data

Description: Clear workspace and load the saved dataset and model from the .mat file.

11. Extract and Normalize Data Again

Description: Re-extract and normalize features from the loaded data using previously saved min and max values.

12. Predict Tool Life for Test Data Using Loaded Model Description: Use the loaded model to make predictions on the test data.

13. Evaluate the Performance of the Loaded Model

Description: Calculate and display the MSE for predictions made by the loaded model.

14. Detailed Testing of the Model Description:

- Plot: Visualize the relationship between actual and predicted tool life.
- Performance Metrics: Calculate and display the R-squared value.

15. Predict Tool Life for New

Data Description:

- New Data: Specify new values for testing.
- Normalize: Apply the same normalization to the new data.
- Predict: Get predictions for new data.
- Display: Show the new predictions.

16. Extract and Normalize Data Again
Description: Re-extract and normalize features from the loaded data using previously saved min and max values.

17. Predict Tool Life for Test Data Using Loaded Model Description: Use the loaded model to make predictions on the test data.
18. Evaluate the Performance of the Loaded Model
Description: Calculate and display the MSE for predictions made by the loaded model.

19. Detailed Testing of the Model Description:
- Plot: Visualize the relationship between actual and predicted tool life.
- Performance Metrics: Calculate and display the R-squared value.

20. Predict Tool Life for New Data Description:
- New Data: Specify new values for testing.
- Normalize: Apply the same normalization to the new data.
- Predict: Get predictions for new data.
- Display: Show the new predictions.

21. Generate Graphs for New Data Description:
Graphs: Visualize tool life predictions based on each feature.

Step	Description	MATLAB Code Snippet
1	Load the dataset	data = readtable('/path/to/file.csv', 'VariableNamingRule', 'preserve');
2	Display the data	disp('Loaded Data:'); disp(data);
3	Extract features and target	X = data{:, 1:end-1}; y = data{:, end};
4	Normalize the features	X = normalize(X, 'range', [0 1]);
5	Split the data	cv = cvpartition(size(X, 1), 'HoldOut', 0.2); ...
6	Create and train the neural network	net = feedforwardnet(10); ...
7	Predict tool life	y_pred = net(X_test');
8	Evaluate model performance	mse_error = mse(net, y_test', y_pred);
9	Save model and parameters	save('file.mat', 'data', 'net', 'X_min', 'X_max');
10	Load model and data	clear data net X y X_train y_train X_test y_test; load('file.mat');
11	Re-extract and normalize data	X = data{:, 1:end-1}; y = data{:, end}; X = (X - X_min) ./ (X_max - X_min);
12	Predict tool life with loaded model	y_pred_loaded = net(X_test');
13	Evaluate the performance of the loaded model	mse_error_loaded = mse(net, y_test', y_pred_loaded);
14	Detailed model testing	scatter(y_test, y_pred_loaded, 'filled'); ...
15	Predict tool life for new data	new_cutting_speeds = [...]; new_feed_rates = [...]; ...
16	Generate graphs for new data	plot(cutting_speed, tool_life, '-o'); ...

Table 2.1 Summary table for procedure

III. RESULTS PER MODEL DATA

3.1 By MATLAB:

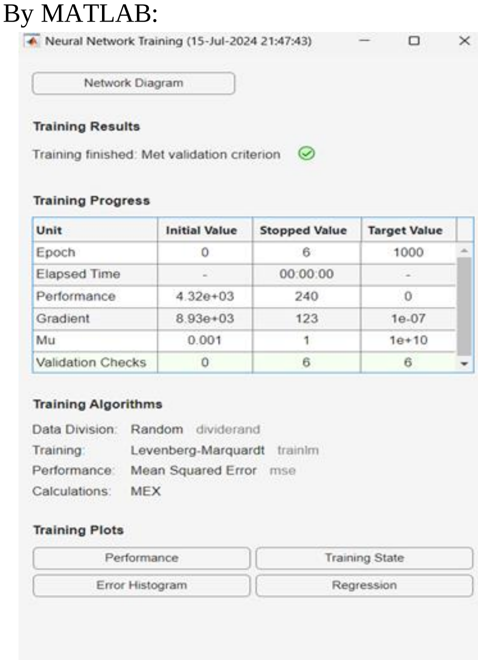

Fig 3.1 Trained model

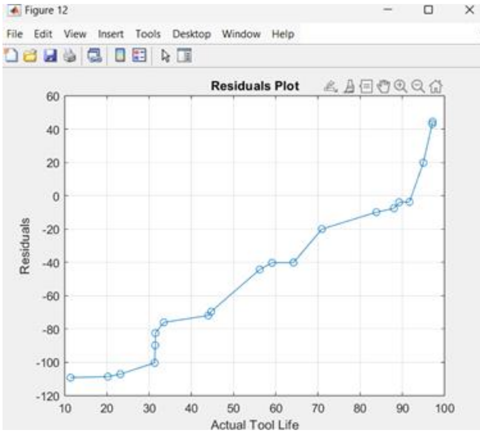

Fig 3.2 Residuals Plot

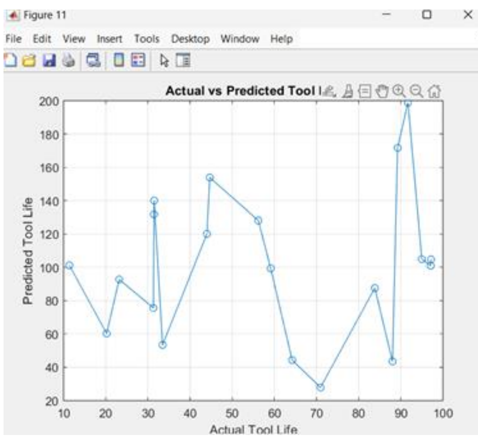

Fig 3.3 Actual vs Predicted Tool life

The size of the residuals noticeably grows as the actual tool life increases, indicating that the prediction errors vary across the range. This inconsistent variance points to the presence of heteroscedasticity, which undermines the assumptions of linear regression and similar models. The model is likely in need of adjustments to better accommodate the nonlinear relationship. Utilizing transformations or investigating more advanced nonlinear models (such as polynomial regression and machine learning techniques) may enhance the predictions. The actual versus predicted plot illustrates a comparison between the predicted tool life values from the model and the related actual tool life values. In a perfectly functioning model, the data points in this plot should be positioned close to the diagonal line where Actual Tool Life equals Predicted Tool Life. Nonetheless.

The points vary considerably from the diagonal line, which suggests a discrepancy between predicted and actual values. There is no consistent correlation, revealing systematic prediction errors. Numerous points, especially those with higher actual tool life values (around 90–100), exhibit extremely large prediction discrepancies. For example, the predicted values either surge or diverge significantly, which may indicate overfitting, inadequate model generalization, or the presence of noisy data. Some mid-range points (actual tool life) also show notable deviations, indicating localized inaccuracies. The erratic zigzag pattern implies that the model lacks robustness and does not effectively capture any underlying patterns in the data. This may stem from the model's reliance on faulty assumptions or insufficient complexity to accurately represent the dynamics of the underlying system.

Model Performance: The combination of the residual plot and the plot comparing actual and predicted values indicates that the model experiences both bias (systematic inaccuracies) and variance (inconsistencies in predictions across different ranges). These challenges diminish its accuracy and dependability. If a linear regression model was applied, it likely fails to capture the nonlinear relationships present in the data. The model might be either overly simplistic to properly represent the data or excessively complex, leading to unpredictability in its predictions. Key factors affecting tool life could be absent, or non- essential features may have been included, which weakens the model's explanatory capabilities. Mistakes during the data collection phase might add to the noise and variability in the predictions. Conduct a more thorough analysis of the data to better understand the relationships, distributions, and possible transformations.

ng Speed (RPM)	Feed Rate (mm/min)	h of Cut (mm)	l Wear (mm)	'ool Life (hours)
1000	150	1.0	0.1	50
1200	200	1.2	0.15	45
1400	250	1.5	0.2	40
1600	180	1.3	0.25	42
1800	210	1.4	0.3	38
ng Speed (RPM)	Feed Rate (mm/min)	h of Cut (mm)	l Wear (mm)	'ool Life (hours)
2000	230	1.6	0.35	35

2200	250	1.5	0.4	33
2400	270	1.7	0.45	30
2600	290	1.8	0.5	28
2800	310	2.0	0.55	25

Table 3.1 Model Dataset for training

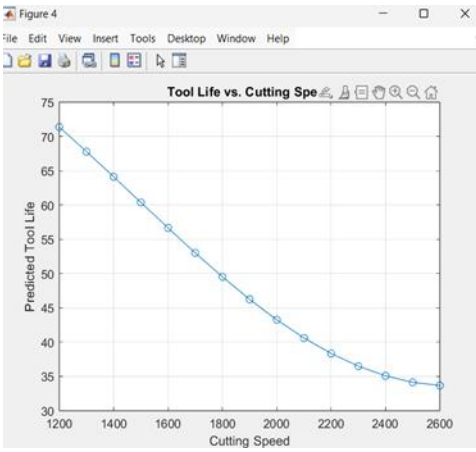

Fig 3.4 Tool life vs Cutting Speed

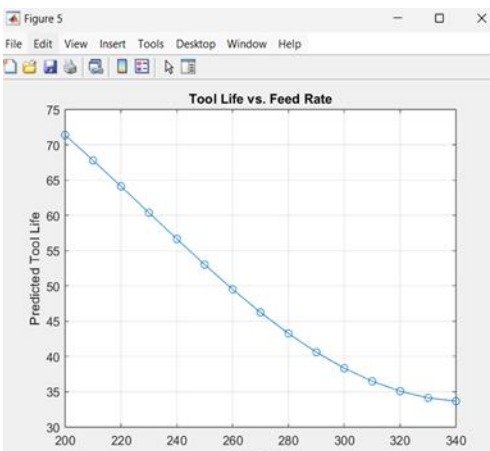

Fig 3.5 Tool life vs Feed Ratio

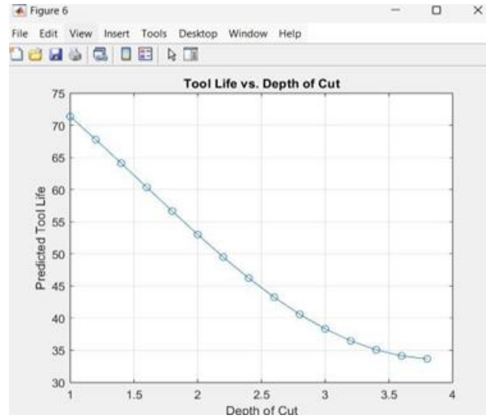

Fig 3.6 Tool life vs Depth of cut

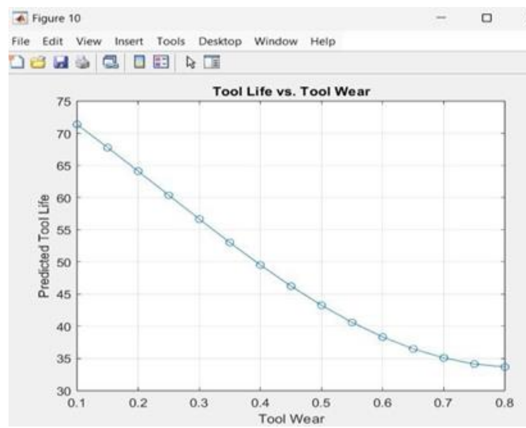

Fig 3.7 Tool life vs Tool Wear

3.2 By using Python and artificial Neural networks in Anaconda software:

Model Dataset:

RPM	Feed Speed	Axial Depth of Cut	Radial Depth of Cut	Tool Life
8470	611	9.094212	2.632166	89.80123
2060	792	4.117126	2.718087	33.48043
6590	918	0.790846	4.513459	11.37741
6391	154	3.536627	0.531524	94.00927
6934	367	6.082292	1.545067	55.09359
7465	652	6.490208	1.040009	58.54397
1666	916	5.172224	1.381289	71.55674
5626	547	4.440492	2.335231	65.4266
6778	1020	5.365459	1.839822	94.95024
9522	944	5.715731	1.936642	94.98264
2885	542	1.211509	3.914538	88.0479

1969	356	3.752959	4.292074	67.27632
8149	164	2.631007	0.509831	82.08544
3633	1007	7.56763	1.119242	70.94515
6511	703	4.638646	3.153031	61.60303
6251	610	9.154124	1.778046	21.56503
7620	840	4.009655	1.31832	83.00838
2384	724	7.6846	1.499279	83.85755
5755	1013	7.525437	1.619223	66.33457
4585	892	1.826314	3.934147	83.83842
7596	390	4.972149	0.801134	68.63363
9866	713	6.623153	3.319208	28.60159
3758	245	8.053557	2.632408	34.6565
9049	883	3.368438	1.504645	29.31302
3247	634	2.438121	2.047036	43.95332
3947	556	6.758116	1.327311	13.50668
1389	380	7.623609	2.89066	65.64285
3934	898	3.568261	0.559014	40.28988
4205	804	1.346354	0.222813	69.01504
5858	320	8.776605	2.962735	44.6857
3099	690	3.998634	1.054805	71.34523
8934	185	5.056212	0.51214	40.65621
2467	674	7.871849	1.945849	33.46251
2728	309	6.446073	0.423382	54.64337
4756	988	6.969902	4.101115	72.36013
5090	848	2.33983	0.321514	41.35029
6593	392	5.264742	2.747006	94.29833
9992	235	6.622903	2.129286	13.52677
9633	945	2.51124	3.156915	47.61514
8713	727	2.039603	1.643872	97.08225
3812	831	9.143081	0.882183	59.31747
8241	706	5.046396	4.5201	48.11238
7435	723	2.795297	3.891307	61.16683
6686	795	9.267033	3.98578	61.83321
8299	945	8.99569	1.301106	75.8483
1975	177	5.412982	0.370873	21.49208
9426	769	8.2672	1.534368	32.50148
4352	705	2.160623	2.563163	62.24896
2785	489	2.954068	1.637265	88.04049
5143	947	6.663149	3.842624	60.568
8755	480	7.950618	1.394789	31.47372
4273	789	8.035654	4.447108	71.18603
2221	655	4.059672	2.211967	76.59179
5043	497	8.312377	3.904902	31.44125
9189	622	7.98817	1.055272	43.9956
8073	380	8.733588	2.009957	58.08947
6875	339	7.410998	3.277854	54.69051
1361	374	6.387097	0.808754	45.06563

5497	534	5.610042	0.78408	36.78717
2195	526	3.776088	4.465962	18.99864
8829	432	8.773174	3.344218	14.81368
2216	782	9.068242	0.380697	96.26873
9069	777	2.998505	1.954812	86.24288
7639	894	3.187202	2.107491	41.94147
9092	408	4.773401	3.473788	96.11208
8063	508	4.446132	1.303786	70.90929
9116	859	9.251226	1.011068	53.42689
9729	605	2.048142	0.555841	54.37231
2078	560	0.659063	2.084584	17.4956
6087	798	4.846265	3.2294	18.25337
6059	467	2.07364	0.456052	64.21968
7531	826	3.724925	4.22694	59.83327
9771	374	7.048701	2.14635	29.14551
9884	968	6.844271	1.255064	95.15751
8408	383	3.210935	0.613042	80.31664
6476	833	5.274354	1.00461	20.21181
3262	813	4.977564	4.312302	93.78362
1264	976	6.099727	3.008391	97.68234
9206	523	2.704064	2.473464	99.63381
3768	821	5.690863	3.09129	15.0284
6663	757	9.114257	2.116961	76.3332
3227	621	4.783331	3.412173	59.13242
3895	382	8.473669	0.409951	73.52483
6458	841	4.32267	2.690564	97.17867
6818	262	3.58069	0.898044	71.9227
7936	979	6.17691	0.728724	85.32675
1591	646	6.386532	1.704271	88.01818
7092	591	8.104675	0.603916	85.46327
4761	713	2.52563	0.614291	48.34823
7384	417	4.892902	1.570219	30.03188
4299	659	5.533637	4.509846	45.69864
7478	956	7.263275	0.971453	90.27072
9592	535	0.883713	0.275509	23.19443
4304	536	9.252044	3.558803	56.19936
8415	262	4.635512	3.750417	30.99053
3654	762	2.960131	1.723739	62.31749
3931	774	8.274747	2.244565	87.68247
9354	230	7.079925	3.059004	89.2324
6256	848	8.887032	0.411459	31.30167
9310	262	3.410603	4.376241	91.69243

Table:3.2 Model dataset for ANN.

Interface

Fig 3.8

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