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Implementation of Multiobjective Optimization of Neural Network for Classification

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ABSTRACT: Hybrid Non-dominated sorting Genetic Algorithm II is used for classification using neural network. This algorithm tries to satisfy two conflicting objectives of neural network classifier i.e. Accuracy and Mean squared Error. To solve classification problem we used Pareto-based multi-objective optimization approach based on an evolutionary algorithm. We proposed hybrid pareto-approach based on NSGA II algorithm. The optimized neural network models can be used for classification. Local search is used to speed the convergence to optimal solutions by augmenting it with genetic algorithm.

The idea is to develop a system capable to solve multi-objective classification problem using Non-dominated Sorting Genetic Algorithm II (NSGA II) by augmenting with back propagation as local search algorithm to deal with disadvantage of genetic algorithm i.e. slow convergence to best solutions. Also optimize the structure of neural network and trained it with respect to accuracy and mean squared error as objectives of given classification problem.

KEYWORDS: Non Dominated Sorting Genetic Algorithm

I. INTRODUCTION

Neural nets take inspiration from the learning process occurring in human brains. They consists of an artificial network of functions, called parameters, which allows the computer to learn, and to fine tune itself, by analyzing new data. Each parameter, sometimes also referred to as neurons, is a function which produces an output, after receiving one or multiple inputs. Those outputs are then passed to the next layer of neurons, which use them as inputs of their own function, and produce further outputs. Those outputs are then passed on to the next layer of neurons, and so it continues until every layer of neurons have been considered, and the terminal neurons have received their input. Those terminal neurons then output the final result for the model.*Figure 2* shows a visual representation of such a network. The initial input is *x*, which is then passed to the first layer of neurons (the h bubbles in *Figure 1)*, where three functions consider the input that they receive, and generate an output. That output is then passed to the second layer (the g bubbles in *Figure 2)*. There further output is calculated, based on the output from the first layer. That secondary output is then combined to yield a final output of the model.

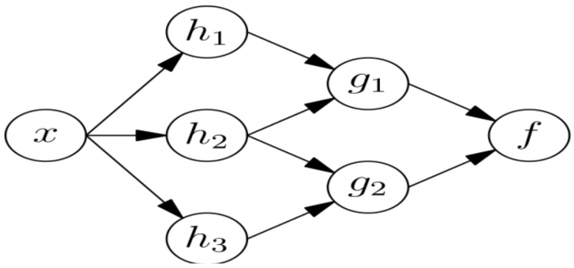

Figure 1: A Visual Representation of a Simple Neural Net

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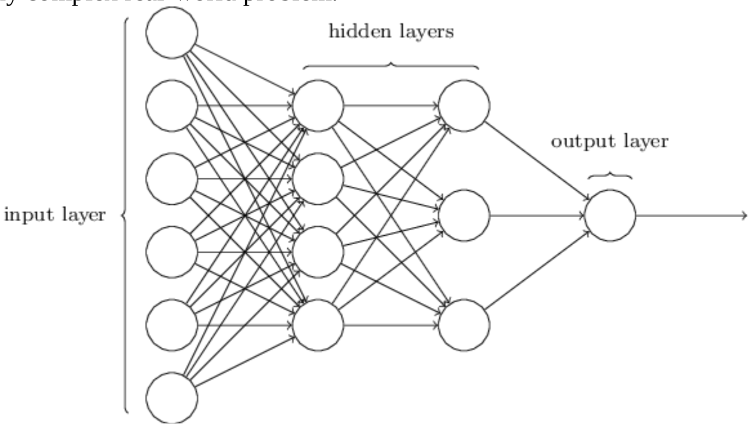
Classification of Neural Network
Different Types of Basics in Classification of Neural Networks

1. Shallow Neural Networks (Collaborative Filtering)
Neural Networks are made of groups of Perceptron to simulate the neural structure of the human brain. Shallow neural networks have a single hidden layer of the perceptron. One of the common examples of shallow neural networks is Collaborative Filtering. The hidden layer of the perceptron would be trained to represent the similarities between entities in order to generate recommendations. Recommendation system in Netflix, Amazon, YouTube, etc. uses a version of Collaborative filtering to recommend their products according to the user interest.

2. Multilayer Perceptron (Deep Neural Networks)
Neural Networks with more than one hidden layer is called Deep Neural Networks. Spoiler Alert! All following neural networks are a form of deep neural network tweaked/improved to tackle domain-specific problems. In general, they help us achieve universality. Given enough number of hidden layers of the neuron, a deep neural network can approximate i.e. solve any complex real-world problem.



The Universal Approximation Theorem is the core of deep neural networks to train and fit any model. Every version of the deep neural network is developed by a fully connected layer of max pooled product of matrix multiplication which is optimized by back propagation algorithms. We will continue to learn the improvements resulting in different forms of deep neural networks.

3. Convolutional Neural Network (CNN)
CNN's are the most mature form of deep neural networks to produce the most accurate i.e. better than human results in computer vision. CNN's are made of layers of Convolutions created by scanning every pixel of images in a dataset. As the data gets approximated layer by layer, CNN's start recognizing the patterns and thereby recognizing the objects in the images. These objects are used extensively in various applications for identification, classification, etc. Recent practices like transfer learning in CNNs have led to significant improvements in the inaccuracy of the models. Google Translator and Google Lens are the most states of the art example of CNN's. The application of CNNs is exponential as they are even used in solving problems that are primarily not related to computer vision.

4. Recurrent Neural Network (RNN)
RNNs are the most recent form of deep neural networks for solving problems in NLP. Simply put, RNNs feed the output of a few hidden layers back to the input layer to aggregate and carry forward the approximation to the next iteration(epoch) of the input dataset. It also helps the model to self-learn and corrects the predictions faster to an extent. Such models are very helpful in understanding the semantics of the text in NLP operations. There are different variants of RNNs like Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU), etc. In the diagram below, the activation from h1 and h2 is fed with input x2 and x3 respectively.

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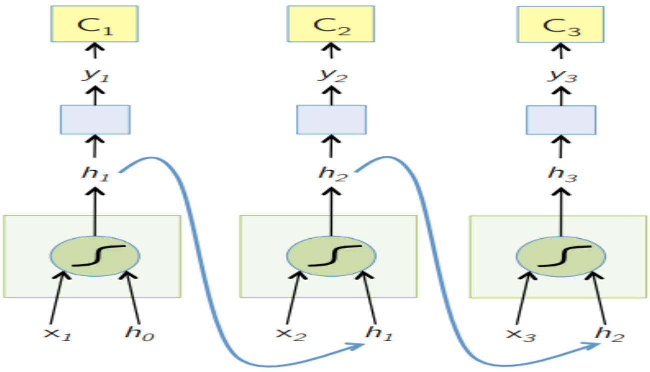
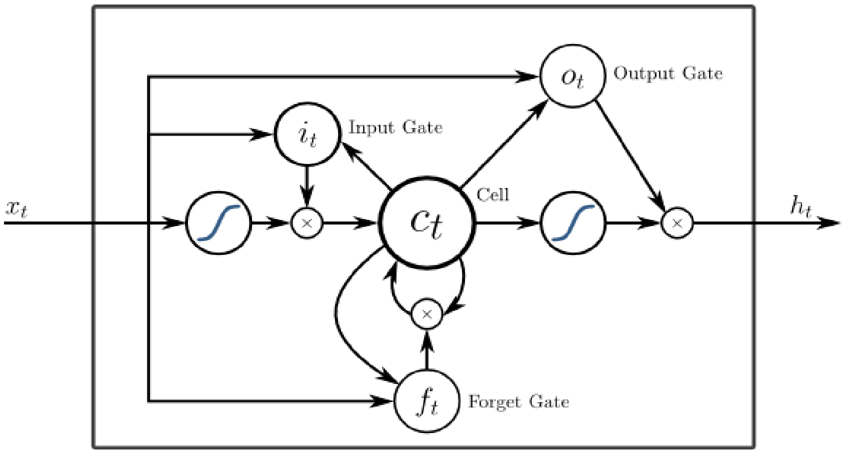


5. Long Short Term Memory (LSTM)

LSTMs are designed specifically to address the vanishing gradients problem with the RNN. Vanishing Gradients happens with large neural networks where the gradients of the loss functions tend to move closer to zero making pausing neural networks to learn. LSTM solves this problem by preventing activation functions within its recurrent components and by having the stored values unmutated. This small change gave big improvements in the final model resulting in tech giants adapting LSTM in their solutions. Over to the "most simple self-explanatory" illustration of LSTM,



6. Attention-based Networks

Attention models are slowly taking over even the new RNNs in practice. The Attention models are built by focusing on part of a subset of the information they're given thereby eliminating the overwhelming amount of background information that is not needed for the task at hand. Attention models are built with a combination of soft and hard attention and fitting by back-propagating soft attention. Multiple attention models stacked hierarchically is called Transformer. These transformers are more efficient to run the stacks in parallel so that they produce state of the art results with comparatively lesser data and time for training the model. An attention distribution becomes very powerful when used with CNN/RNN and can produce text description to an image as follow

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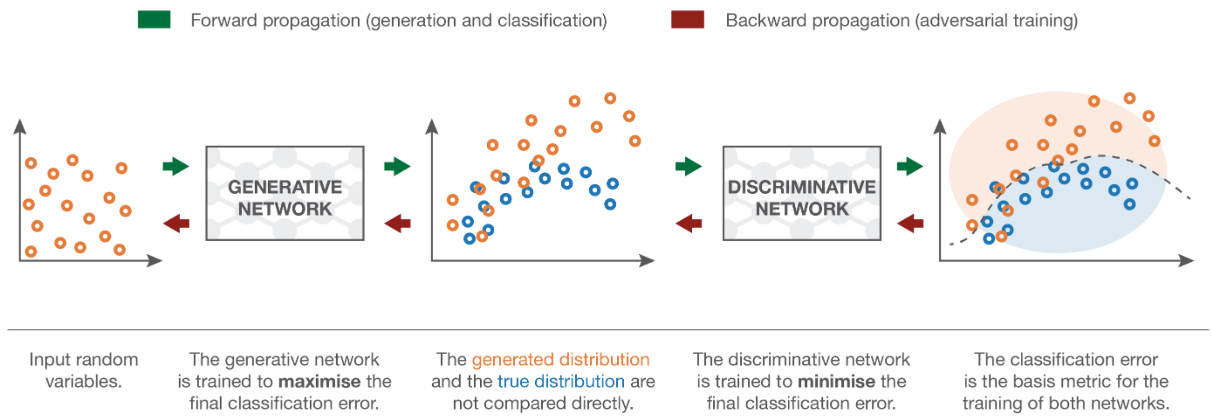
7. Generative Adversarial Network (GAN)

Although deep learning models provide state of the art results, they can be fooled by far more intelligent human counterparts by adding noise to the real-world data. GANs are the latest development in deep learning to tackle such scenarios. GANs use Unsupervised learning where deep neural networks trained with the data generated by an AI model along with the actual dataset to

improve the accuracy and efficiency of the model. These adversarial data are mostly used to fool the discriminatory model in order to build an optimal model. The resulting model tends to be a better approximation than can overcome such noise. The research interest in GANs has led to more sophisticated implementations like Conditional GAN (CGAN), Laplacian Pyramid GAN (LAPGAN), Super Resolution GAN (SRGAN), etc.



Classification:

Classification can be defined as the grouping of things by shared features, characteristics and qualities or if you will simply dropping things into corresponding buckets, you could for instance classify the following geometric shapes based on their similarity.

Classification involves predicting which class an item belongs to. Some classifiers are binary, resulting in a yes/no decision. Others are multi-class, able to categorize an item into one of several categories. Classification is a very common use case of machine learning—classification algorithms are used to solve problems like email spam filtering, document categorization, speech recognition, image recognition, and handwriting recognition.

In this context, a neural network is one of several machine learning algorithms that can help solve classification problems. Its unique strength is its ability to dynamically create complex prediction functions, and emulate human thinking, in a way that no other algorithm can. There are many classification problems for which neural networks have yielded the best results.

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Basic Terminology in Classification Algorithms

- **Classifier:** An algorithm that maps the input data to a specific category.
- **Classification model:** A classification model tries to draw some conclusion from the input values given for training. It will predict the class labels/categories for the new data.
- **Feature:** A feature is an individual measurable property of a phenomenon being observed.
- **Binary Classification:** Classification task with two possible outcomes. **Eg: Gender classification (Male / Female)**
- **Multi-class classification:** Classification with more than two classes. In multi-class classification, each sample is assigned to one and only one target label. **Eg: An animal can be a cat or dog but not both at the same time.**
- **Multi-label classification:** Classification task where each sample is mapped to a set of target labels (more than one class). **Eg: A news article can be about sports, a person, and location at the same time.**

Applications of Classification Algorithms

- Email spam classification
- Bank customers loan pay willingness prediction.
- Cancer tumor cells identification.
- Sentiment analysis
- Drugs classification
- Facial key points detection
- Pedestrians detection in an automotive car driving.

Types of Classification Algorithms

Classification Algorithms could be broadly classified as the following:

- **Linear Classifiers**
    - Logistic regression
    - Naive Bayes classifier
    - Fisher's linear discriminant
- **Support vector machines**
    - Least squares support vector machines
- **Quadratic classifiers**
- **Kernel estimation**
    - k-nearest neighbor
- **Decision trees**
    - Random forests

II. RELATED WORK

1. MULTI-OBJECTIVE OPTIMIZATION OF A STACKED NEURAL NETWORK USING AN EVOLUTIONARY HYPER-HEURISTIC HEURISTIC.

The proposed hyper-heuristic is based on the NSGA-II (Non-dominated Sorting Genetic Algorithm – II) multi-objective optimization evolutionary algorithm which incorporates the Quasi-Newton (QN) optimization algorithm. QN is used for training each neural network from the stack. The final global optimal solution provided by NSGA-II-QNSNN algorithm is a Pareto optimal front. It represents all the equally good compromises that can be made between the structural complexity of the stacked neural network and its modelling performance. The set of decision variables, which led to obtaining the set of points in the Pareto optimal front, represents the optimum values for the parameters of the stacked neural network: the number of networks in the stack, the weights for every output of the composing

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networks, and the number of hidden neurons in each individual neural network. Each stacked neural network determined through the optimization process was trained and tested by applying it to a real world problem: the modelling of the polyacrylamide-based multicomponent hydrogels synthesis. The neural modelling established the influence of the reaction conditions on the reaction yield and the swelling degree. The results provided by NSGA-II-QNSNN were superior, not only in terms of performance, but also in terms of structural complexity, to those obtained in our previous works, where individual or aggregated neural networks were used, but the stacks were developed manually, based on successive trials.

2. MULTI-OBJECTIVE OPTIMIZATION FOR BUILDING RETROFIT: A MODEL USING GENETIC ALGORITHM AND ARTIFICIAL NEURAL NETWORK AND AN APPLICATION

This paper presents a multi-objective optimization model using genetic algorithm (GA) and artificial neural network (ANN) to quantitatively assess technology choices in a building retrofit project. This model combines the rapidity of evaluation of ANNs with the optimization power of GAs. A school building is used as a case study to demonstrate the practicability of the proposed approach and highlight potential problems that may arise. The study starts with the individual optimization of objective functions focusing on building's characteristics and performance: energy consumption, retrofit cost, and thermal discomfort hours. Then a multi-objective optimization model is developed to study the interaction between these conflicting objectives and assess their trade-offs.

3. EVOLUTIONARY MULTI-OBJECTIVE OPTIMIZATION OF NEURAL NETWORKS FOR FACE DETECTION

This paper describes the optimization of such a NN by a hybrid algorithm combining evolutionary multi-objective optimization (EMO) and gradient-based learning. The evolved solutions perform considerably faster than an expert-designed architecture without loss of accuracy. We compare an EMO and a single objective approach, both with online search strategy adaptation. It turns out that EMO is preferable to the single objective approach in several respects

4. A MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM USING NEURAL NETWORKS TO APPROXIMATE FITNESS EVALUATIONS

In this paper two different methods to accelerate the search of a Multi-Objective Evolutionary Algorithm (MOEA) using Artificial Neural Networks are presented. Two different methods are proposed. One using ANN to approximate the fitness of the solutions alternated with the real fitness evaluation, being the ANN approximation used only when the estimated error of the neural network was lower than a pre-defined value. In the second method, the ANN is used as a local search strategy by defining new better solutions from the precedent generation. These methods can substantially reduce the number of fitness evaluations on computational expensive problems while not compromise the good search capabilities of MOEA. The efficiency of the methods proposed is tested on several benchmark functions as well on a real multi-optimization problem of polymer extrusion.

5. MULTI-TASK LEARNING AS MULTI-OBJECTIVE OPTIMIZATION

In this paper, we explicitly cast multi-task learning as multi-objective optimization, with the overall objective of finding a Pareto optimal solution. To this end, we use algorithms developed in the gradient-based multi-objective optimization literature. These algorithms are not directly applicable to large-scale learning problems since they scale poorly with the dimensionality of the gradients and the number of tasks. We therefore propose an upper bound for the multi-objective loss and show that it can be optimized efficiently. We further prove that optimizing this upper bound yields a Pareto optimal solution under realistic assumptions. We apply our method to a variety of multi-task deep learning problems including digit classification, scene understanding (joint semantic segmentation, instance segmentation, and depth estimation), and multilabel classification. Our method produces higher-performing models than recent multi-task learning formulations or per-task training.

6. EVOLUTIONARY MULTI-OBJECTIVE OPTIMIZATION OF SPIKING NEURAL NETWORKS

Evolutionary multi-objective optimization of spiking neural networks for solving classification problems is studied in this paper. By means of a Paretobased multi-objective genetic algorithm, we are able to optimize both classification performance and connectivity of spiking neural networks with the latency coding. During optimization, the

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connectivity between two neurons, i.e., whether two neurons are connected, and if connected, both weight and delay between the two neurons, are evolved. We minimize the the classification error in percentage or the root mean square error for optimizing performance, and minimize the number of connections or the sum of delays for connectivity to investigate the influence of the objectives on the performance and connectivity of spiking neural networks. Simulation results on two benchmarks show that Pareto-based evolutionary optimization of spiking neural networks is able to offer a deeper insight into the properties of the spiking neural networks and the problem at hand.

7. MULTI-OBJECTIVE OPTIMIZATION BY MEANS OF MULTI-DIMENSIONAL MLP NEURAL NETWORKS

In this paper, a multi-layer perceptron (MLP) neural network (NN) is put forward as an efficient tool for performing two tasks: 1) optimization of multi-objective problems and 2) solving a non-linear system of equations. In both cases, mathematical functions which are continuous and partially bounded are involved. Previously, these two tasks were performed by recurrent neural networks and also strong algorithms like evolutionary ones. In this study, multi-dimensional structure in the output layer of the MLP-NN, as an innovative method, is utilized to implicitly optimize the multivariate functions under the network energy optimization mechanism. To this end, the activation functions in the output layer are replaced with the multivariate functions intended to be optimized. The effective training parameters in the global search are surveyed. Also, it is demonstrated that the MLP-NN with proper dynamic learning rate is able to find globally optimal solutions. Finally, the efficiency of the MLP-NN in both aspects of speed and power is investigated by some well-known experimental examples. In some of these examples, the proposed method gives explicitly better globally optimal solutions compared to that of the other references and also shows completely satisfactory results in other experiments.

8. MULTI-OBJECTIVE OPTIMIZATION IN ELECTRIC DISCHARGE MACHINING OF ALUMINIUM COMPOSITE.

This paper involves the optimization of input process parameters in Electric Discharge Machining of Aluminium hybrid Metal Matrix Composite. Aluminium AlSi10Mg alloy reinforced with 9 %wt. alumina and 3 %wt. graphite particles fabricated through liquid metallurgy route was used for machining. Experiments were conducted in an Electric Discharge Machine and the influence of input process parameters such as Peak current, Pulse-on time and Flushing pressure during machining of aluminium composite was studied. The objective was to obtain a minimum surface roughness with minimum tool wear rate and maximum material removal rate. Multi-objective optimization of the input process parameters was performed by employing Artificial Neural Network and Genetic Algorithm hybrid optimization technique. The results obtained provide a pareto-optimal solution set that offers a set of non-dominated solutions that can be used in a practical situation by a decision maker

9. ARTIFICIAL NEURAL NETWORKS AS METAMODELS FOR THE MULTIOBJECTIVE OPTIMIZATION OF BIOBUTANOL PRODUCTION.

Process optimization using a physical process or its comprehensive model often requires a significant amount of time. To remedy this problem, met models, or surrogate models, can be used. In this investigation, a methodology for optimizing the biobutanol production process via the integrated acetone–butanol–ethanol (ABE) fermentation–membrane pervaporation process is proposed. In this investigation, artificial neural networks (ANNs) were used as meta models in an attempt to reduce the time needed to circumscribe the Pareto domain and identify the best optimal operating conditions. Two different met models were derived from a small set of operating conditions obtained from a uniform experimental design. The first series of meta models were derived to entirely replace the phenomenological model of the butanol fermentation process by representing the relationship that exists between five operating conditions and four performance criteria. The second series of meta models were derived to estimate the initial concentrations under steady-state conditions for the eight chemical species within the fermenter in order to expedite convergence of the process simulator. The first series of meta models led to an accurate Pareto domain and reduced the computation time to circumscribe the Pareto domain by a factor of 2500. The second series of metamodels led to only a small reduction of computation time because of the inherently slow convergence of the overall fermentation process.

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III. IMPLEMENTATION & TESTING

Architecture Diagram shows the architecture diagram for proposed sys-tem. We consider different classification problems from UCI repository. Input parameters like number of generations, population size, set of objectives which are to be optimized i.e. Accuracy and Mean Squared error. Also neural network parameters are given as decision variables. System consists of different modules like Random population generation, Training and Evaluation, Non-dominated sorting, Crowding distance, Elitism, Reproduction and Local search. Our approach is first to define neural network models using decision variables and then train all defined neural networks using Non-dominated Sorting Genetic Algorithm II (NSGA II) and back propagation by maximizing accuracy and minimizing mean squared error for given problem. Test all trained neural network models on respective dataset and calculate both objectives and find best neural network models having higher accuracy and low mean squared error.

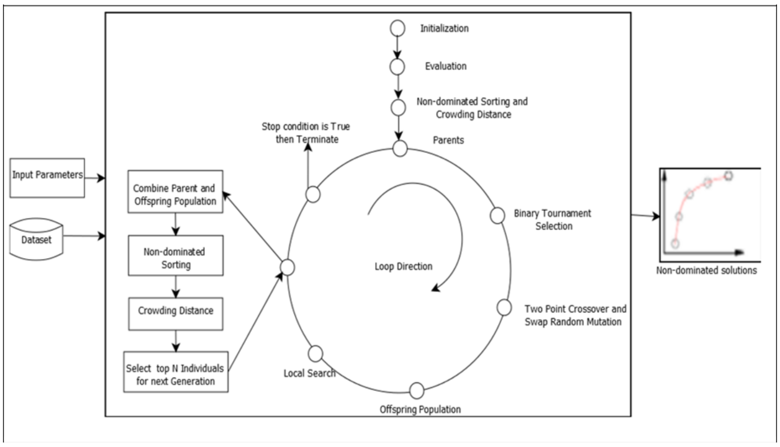

Figure 3.2: Architecture Diagram

Flow chart of the Application.

1. Select training data set
2. Set population size (All possible solutions of given problem)
3. Analysis of data
4. Calculate mean square error & accuracy.
5. Find the perfect fitness function.
6. Apply crossover
7. Apply mutation.
8. Survivor selection
9. Terminate condition

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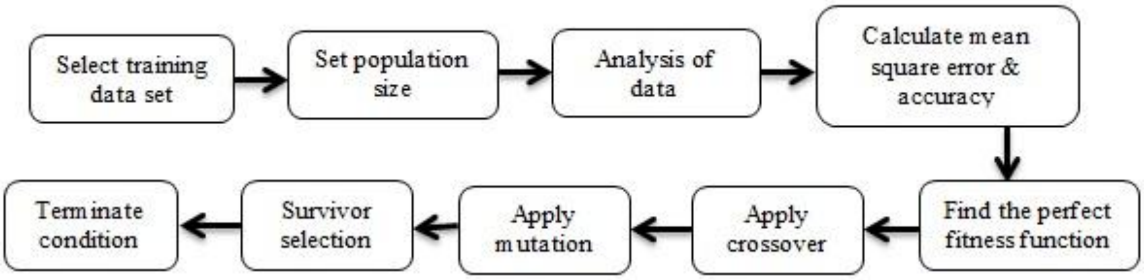

Figure 3.1: Flowchart of the application

Test Cases and Test Results

Unit Testing: In Unit testing we select Hybrid NSGAII algorithm as unit .The input of our system is the dataset that we are selecting is shown below

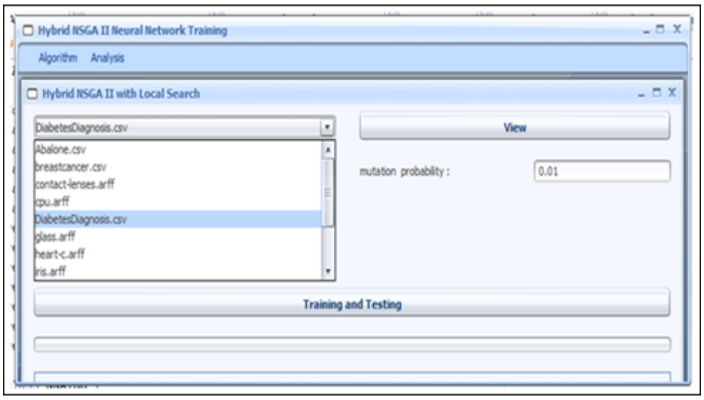

Figure 3.2: Unit Testing for Hybrid NSGAII Dataset selection After givin dataset as input.

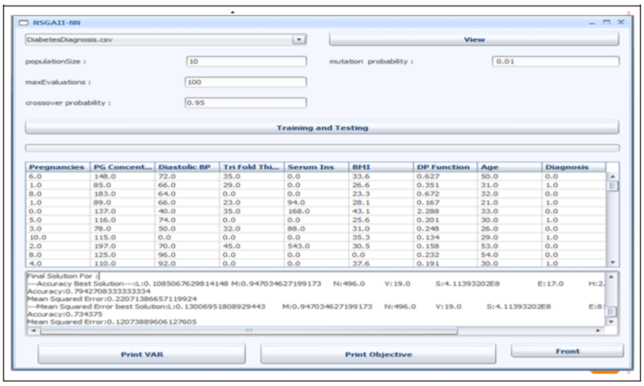

Figure 3.3: Dataset Viewed On Selected Dataset, Training and Testing is applied.

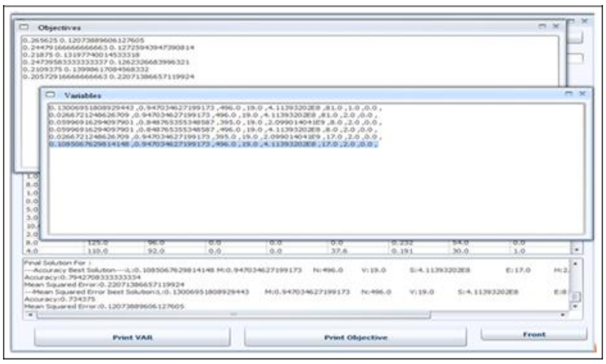

Figure3.4: Actual Result

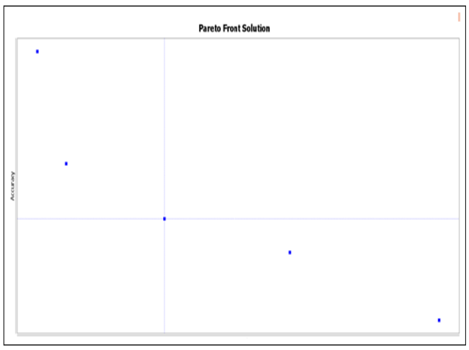

Fig.3.5 Actual Graph

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IV. RESULT AND SCREENSHOTS

To check and analyse the result we are considering the various instances of datasets along with the attributes for different problem statements. So to understand the result in better way we have consider the dataset instances of problems such as Weather forecast, Diabetes diagnosis, Breast cancer, Contact lenses, new-thyroid, etc.
We are going to analyse data set for various problem from different domains the details of datasets, their attributes and associated instances are specified as follow.

Table 4.1: Sample data sets, Attributes and associated instances

Sr. No.	Dataset	Attributes	Instances	Sr. No.	Dataset	Attributes	Instances
1	Abalone	9	9	**7**	Heart-c	14	303
2	Breast Cancer	10	699	**8**	Iris	5	50
3	Contact-lenses	5	24	**9**	Liver-disorders	7	345
4	CPU	7	209	**10**	New thyroid	6	21
5	Diabetes Diagnosis	9	768	**11**	Weather	5	14
6	Glass	10	214	**12**	Wine	14	178

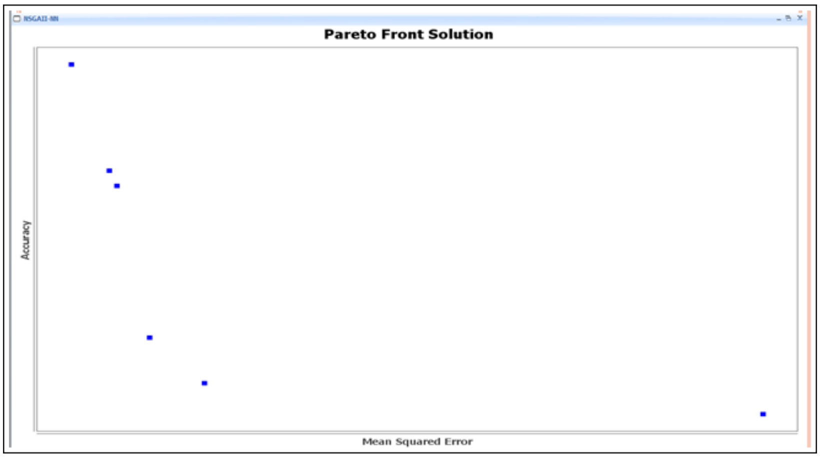

Figure 4.1: Pareto Front solution showing Accuracy and Mean Squared Error for the given datasets.

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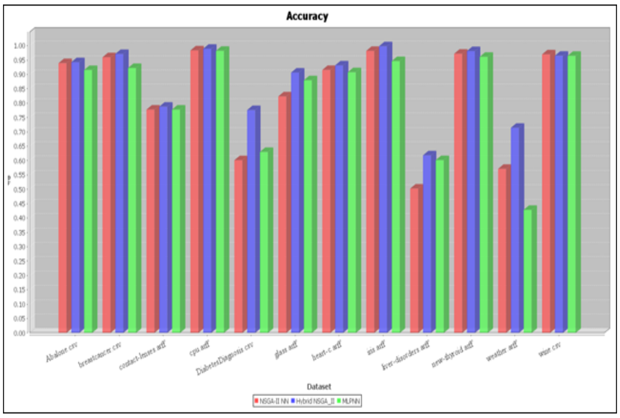

Figure 4.2: Graph Analysis for the given datasets-1.

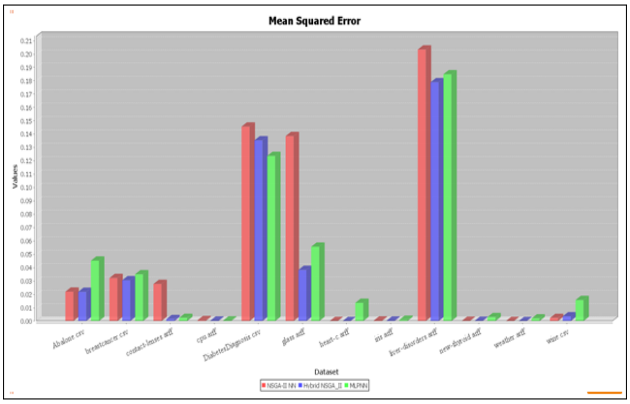

Figure4.3: Graph Analysis for the Mean Squared Error parameter given datasets-1.

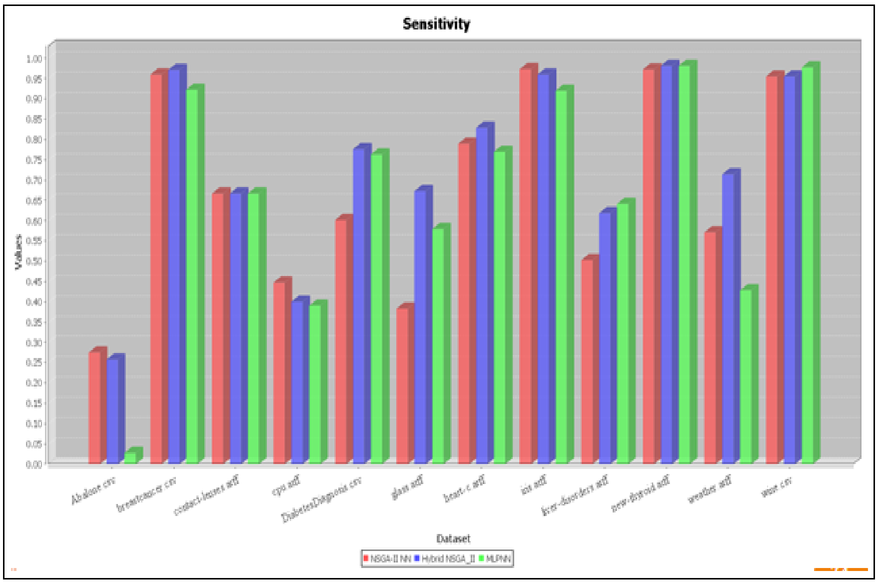

Figure4.4: Graph Analysis for the Sensitivity parameter given datasets-1.

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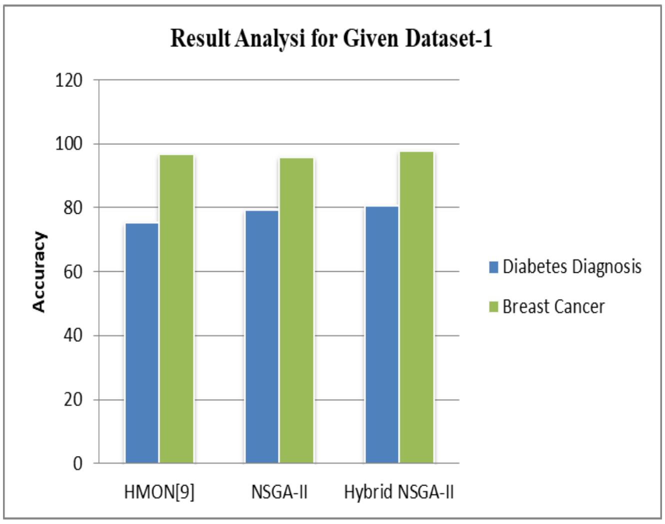
4.2 Result Analysis for Accuracy parameters of different datasets.

Table 4.2.1 Result Analysis for Accuracy Parameter

Datasets	HMON[9]	NSGA-II	Hybrid NSGA-II
Diabetes Diagnosis	75.36	79.43	80.73
Breast Cancer	96.82	96	97.99



Datasets	MOGATTBPN	MEPGANfif2 [10]	MEPGANfif3 [10]	NSGA-II	Hybrid NSGA-II
IRIS	77.55	83.78	84.44	97.33	99.8
WINE	74.29	72.18	72.04	97	96.5
YEAST	90.01	90	90.01	90.67	92.95

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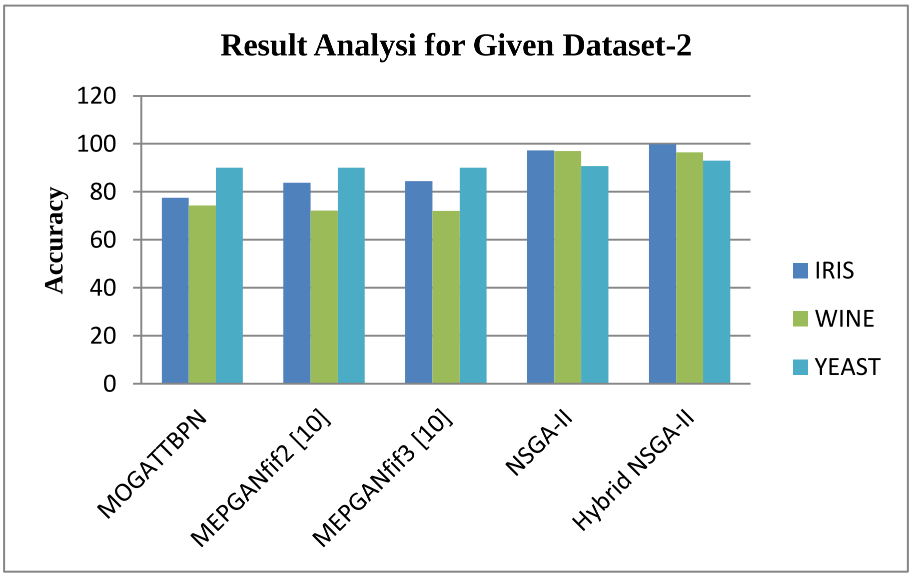

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V. CONCLUSION AND FUTURE WORK

The main objective of our project is to optimize the neural network models and use best optimal neural network models to solve different classification problems by simultaneously satisfying Accuracy and Mean Squared Error as conflicting objectives of respective problem. For optimization of neural networks and solving of classification problem we use Non-dominated Sorting Genetic Algorithm II. The disadvantage of evolutionary algorithm is slow convergence to best solutions. Back propagation is used as local search technique to speed slow convergence. Our system is able to solve different classification problems and gives set of optimal solutions. However, user interaction is required for selection of datasets and differentparameters like population size, no. of generations, crossover probability and mutation probability. We have carried out rigorous experimentation on different datasets. Solve 12 classification problems using three different methods i.e. Multilayer Perceptron Neural Network, Non-dominated Sorting Genetic Algorithm II and Hybrid Non-dominated Sorting Genetic Algorithm II. We have compared the results of three methods for 12 datasets for performance measures Accuracy, Mean Squared Error, Sensitivity, Specificity and Time. Also we compared results with existing system. Our system gives best results for all classification problems. As we solved different classification problems from different fields. Our System will help doctors, researchers, in different companies for decision making.

Future Scope:
Consider more than two objectives for optimization as we have considered only Accuracy and Mean Squared Error objectives for optimization. For future work more than two objectives can be considered like Sensitivity, Precision and Recall etc. In future work will be extended for unbalanced Datasets. Data Pre-processing: Data discretization using methods like normalization or linear transformations can be used to create a homogeneous chromosome structure.

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