DEEP LEARNING FOR OPTIMAL DECISION MAKING ORIENTED PREDICTION FOR COMBINATORIAL OPTIMIZATION PROBLEM

BY

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project/internship titled **“Deep learning for optimal decision making oriented prediction for combinatorial optimization problem”**, submitted by Thaharim Khan, ID No: 201-25-879 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 12/09/2021.

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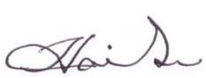

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DECLARATION

I hereby declare that, this project has been done by us under the supervision of **Dr. Sheak Rashed Haider Noori, Associate Professor and Associate Head, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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Finally, I must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

In the field of Computer Science, the growing advancement help the researchers a lot to confront the new problems and making a new solution. Not only with the existing algorithm but also various ways can be found for making a solution. This could be either mathematically or logically. This work proposed a method for using deep learning for solving the combinatorial optimization problem. Combinatorial optimization problem is very much hard in nature and very much difficult to solve or compute mathematically. This proposed work helps to find the optimization with the help of deep learning. This work mainly focuses on a problem which is considered as data point and find out the optimal solution with the help of deep learning for the given task.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Combinatorial optimization problem such an optimization wherein the possible answers may be expressed the use of standards from combinatorics which may be the inclusive of sets, subsets, terms of mathematics like permutations again related terms of graph theory can also be added in this place like inclusive of vertices, edges, cliques, paths, cycles or cuts. One of the most known topic is linear program which is also used in combinatorial optimization termed as 0-1 linear program. Linear Programs with the extra restrict that the variables need to take binary values. On other hand combinatorial optimization is a unique case of discrete optimization which simply approach optimizing over a discrete set [1]. There may have a finite set of solutions for a problem combinatorial optimization find the best optimal solution among from the fine set of solution. In the field of computer science, applied mathematics, operation research in all these sector this combinatorial optimization use in a large extend. In the field of Computer science Now-a-days machine learning is one of most trend topic , use combinatorial optimization in some extend for developing the heuristics and metaheuristics algorithm. For solving the problem by the means of Machine learning a frame work at first developed which is an agent based framework work with the principals of machine learning architecture such as the architecture for the training data set the approaches for the testing part of the dataset. This proposed work is done for making a combination of deep leaning and combinatorial optimization for solving various solutions. In this work Deep learning approaches are used for making a better solution for the noisy data as well as which is done in a general means. It is appropriate for common signs for which no unmistakable numerical detailing arises in light of the fact that the genuine information circulation isn't referred to systematically, for example, when handling pictures, text, voice or atoms, or on the other hand with recommender frameworks, informal communities or predictions of financial means .

1.2 Motivation

Deep learning can help upgrade an algorithm on a circulation of different issues by the dint of combinatorial improvement. On the solitary side, the scientist expects proficient information roughly the improvement calculation, anyway wants to refresh a couple of hefty calculations with the guide of utilizing a speedy estimate. Learning might be utilized to build such approximations in a typical manner. On the elective side, proficient experience probably won't be sufficient and a couple of algorithmic decisions can likewise also be unsuitable. The aim is thus to find the distance of those decisions, and break down out of this revel in the wonderful acting conduct (strategy), ideally upgrading at the best in class. In this proposed work, we will uncover by means of the models reviewed on this paper that this does now presently don't efficiently infer that fusing becoming acquainted with will bargain by and large hypothetical assurances. This proposed work give us the arrangement that to resolve a combinatorial issue, combinatorial enhancement can break down the issue into more modest, just as less complex undertakings. The combinatorial advancement shape thus goes about as an important prior for the model. It's anything but a likelihood to use the combinatorial advancement writing, considerably in expressions of hypothetical certifications

1.3 Rationale of the study

Combinatorial optimization is a solution that includes locating an optimal objects from a finite set of objects. In the field of statistics and computer science there is various search exists like as exhaustive search which isn't always tractable can be done through combinatorial optimization. Deep learning, Machine learning all these topic are added a new era in the field of research. All the possible areas where deep learning produce a better result there the Combinatorial optimization can added a new dimensions with optimality . It operates at the area of these optimization issues wherein the set of possible solutions is discrete or may be decreased to discrete, and wherein the aim is to discover the nice solution. This proposed work mainly work on finding a optimization problem with the help of deep learning and combinatorial optimization for the solution this proposed work consider the conventional issues as information focuses and discover what is the applicable appropriation of the issue to utilize the learning on the given undertaking .

1.4 Research Question

Combinatorial optimization is the technique of trying to get the maximum or minimum from a function F whose area is a discrete however big configuration space in place of an N-dimensional non-stop space as like as we can consider the travelling salesman problem the most common example where we can consider to find the (x, y) positions from the N different cities. So optimality must come in this section. With the Deep learning architecture the solution can be made more optimal .The question is

How the optimal solution can be made through this work?

How this work can be more effective in the field of Deep learning?

1.5 Expected Outcome

The primary objective of this proposed work is to focus on a combinatorial improvement calculations that discover the information on an assigned implied appropriation of issues. Fusing Deep learning added substances in the calculation can acquire this. At last, the implied information extricated by Deep learning calculations is correlative to the hard-won express skill separated through CO exploration. Maybe, it intends to expand and mechanize the unwritten master instinct (or absence of) on different existing calculations of Deep learning .Most of the occasions, the learning issue has a measurable detailing that is tackled through numerical advancement. As of late, emotional advancement has been accomplished with Deep learning, a ML sub-field assembling enormous parametric approximates by making less difficult capacities. Deep learning dominates when applied in high dimensional spaces with countless information focuses

1.6 Project Management

For implementing the proposed work we need

- 8 GB Ram
- Anaconda prompt (anaconda 3)
- Jupyter notebook
- At least 4 GB Memory

1.7 Proposed Layout of Report

Chapter 1: Introduction

Introduction, Motivation, Rationale of the Study, Research Questions, Expected Output, Project Management and Report Layout all of these topics are covered in this section .

Chapter 2: Background

Terminologies, Related Works, Comparative Analysis and Summary, Scope of the Problem and Challenges are elaborately discussed in this section.

Chapter 3: Research Methodology

The overall procedure of completing the proposed work or the way of the work is discussed here step by step. Methods and steps, data collection procedure, some statistical analysis of the proposed system all of these topics are covered in this section with elaboration.

Chapter 4: Experimental results and discussion

Final Outcome of the proposed work is discussed here with proper justification and also discuss about how to enhance the performance more.

Chapter 5: Summary, Conclusion, Recommendation and Implication for Future Research

This section mainly conclude the proposed work with references. Also the planning with this work which we need to execute in future is discussed here .

Chapter 2

Background

2.1 Introduction

Combinatorial optimization is one of the most popular solution for finding the optimal solution in the field of mathematics. When it is combined with the Deep learning architecture then the solution and availability of the accuracy become more appreciated.

Combinatorial optimizations with machine learning is done before with large extend and give the better accuracy than the usual formation. This proposed work is for getting the better accuracy for combinatorial optimization with the Deep learning model.

In this unique situation, the quantity of distributions on Combinatorial streamlining issues has expanded essentially as of late (8,393 out of 2019, cf. Segment 3.1), with more than 150 audits regarding the matter. Be that as it may, these audits just cover certain parts of CO: for instance, there are numerous surveys on explicit Combinatorial streamlining issues like the quadratic task issue (Loiola et al., 2007), the dynamic (Pillac et al., 2013) and the multi-objective (Jozefowiez et al., 2008) vehicle steering issue, the area directing issue (Nagy and Salhi, 2007; Prodhon and Prins, 2014) or the base crossing tree issue (Pop, 2020). Moreover, numerous examinations audit metaheuristics in Combinatorial streamlining by and large (Blum and Roli, 2003; Gendreau and Potvin, 2005) or in correlation with one another in regards to a particular issue (for example mobile sales rep issue (Halim and Ismail, 2019)). Also, specific metaheuristics like subterranean insect state enhancement (Blum, 2005), other arrangement calculations like Benders disintegration (Rahmaniani et al., 2017) just as genuine uses of Combinatorial improvement (for example economical store network plan (Eskandarpour et al., 2015)) are surveyed.

Scientists in CO investigate the underlying highlights of the issues and utilize these highlights to foster both exact and rough broad arrangement procedures. Normally these CO issues are classified dependent on their computational intricacy. In any case, this most pessimistic scenario assessment doesn't generally mirror the real computational attainability; the genuine trouble of the issues drives the improvement of arrangement draws near (Bjorndal et al., 1995). Through the improvement of successful techniques and inventive methodologies, hard true issues would already be able to be settled all the more productively.

2.2 Related Works

Nagarajan, P., Warnell, G. *et.al* [2] proposed a methodology where they are dealing with deep reinforcement learning, and find some challenges in training process. They are discussing about the high-quality influences of deterministic implementations in removing nondeterminism in training. To do so, they remember the precise case of the deep Q-learninng algorithm, for which they produce a deterministic implementation via way of means of figuring out and controlling all assets of nondeterminism in the training process.

Ravi.S *et.al.* [3] The general conviction is that gradient- based optimization in high limit classifiers requires numerous iterative strides over numerous guides to perform well. In this work they propose a LSTM based meta-student model to become familiar with the specific advancement calculation used to prepare another student neural organization classifier in the couple of shot system.

Smith, K. A *et.al.* [4] Proposed an article which sums up the work that has been done and presents the current remaining of neural organizations for combinatorial advancement by thinking about every one of the significant classes of combinatorial streamlining issues.

Sutton R.S. *et.al.* [5] Proposed a book where they have investigate a computational way to deal with gaining from cooperation. Maybe than straightforwardly guessing about how individuals or creatures learn, we investigate romanticized learning circumstances and assess the viability of different learning strategies.

Murphy *et.al.* [6] Proposed a book where they discussed about the development of data analytics with Artificial intelligence .AI gives these, creating techniques that can consequently distinguish designs in information and afterward utilize the revealed examples to anticipate future information. This proposed book offers an extensive and independent prologue to the field of AI, in view of a brought together, probabilistic methodology.

Marcos Alvarez *et.al.* [7] Present in this paper another nonexclusive way to deal with variable spreading in branch and headed for blended whole number straight issues. Our methodology comprises in mimicking the choices taken by a decent expanding system, in particular solid spreading, with a quick estimate. This approximated work is made by an AI strategy from a bunch of noticed spreading choices taken by solid expanding

2.3 Comparative Analysis and Summary

Deep learning investigation have made different methodologies to deal with the collection of coordinated arrangement of Data in a manner that can manage variable-size data structures, e.g., variable-length progressions. We outline different occupations of deep figuring out how to assist with handling combinatorial improvement issues and sort out them along two symmetrical tomahawks. Regardless, in Section 3.1 we layout the two essential motivations for using learning: gauge additionally, disclosure of new methodologies. By then, in Section 3.2, we show occurrences of different ways to deal with solidify learned and standard algorithmic segments.

2.4 Scope of the Problem

This implemented idea work well on level of measurement and classifier which is mainly rank based.This type of combinatorial optimization could be used. Again this combinatorial optimization solution can be used confidence-based and non-confidence based function. With this optimized solution this proposed system can get more averaged result than a sum combiner. Combinatorial optimization issues can be seen as looking for the best component of some arrangement of discrete things; in this manner, on a fundamental level, such a pursuit calculation or metaheuristic can be utilized to address them.

2.5 Challenges

One of the principle challenges of mathematicians engaged in combinatorics is that of enumerating. For a given arrangement of articles, the number of these items have certain properties? For instance, among all diagrams with p focuses, what number of these are no isomorphic trees? Such specification issues, nonetheless, don't just emerge in unadulterated arithmetic but on the other hand are experienced in different parts of regular sciences just as in ordinary life. A player thinking about potential systems should appraise certain

Chapter 3

Research Methodology

3.1 Introduction

For finding the combinatorial Optimization in the field of deep learning we used to do a deep learning research work on a data set. As the deep learning produce better result on image net for this we are using a data set of mango leaves with disease. Where at first we used to do the endeavor of disease detection and trying to find the accuracy using deep learning classifier. After that implementing the resultant output with combinatorial optimization. Below figure 3.1 Illustrates the working principals of Deep learning part

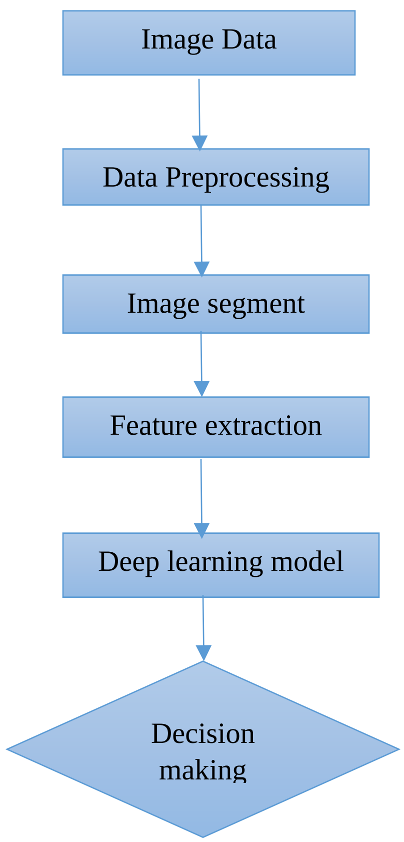

Figure 3.1: Working procedure for of Deep learning part the proposed framework

Fig 3.1 depict the partial working procedure for the proposed frame work. From this figure we get to know the working principal for the Deep learning part

3.2 Data Collection Procedure

To build up the first dataset, the entire mango leaf was shoot. Around 1000 pictures were accepted command over a few days. Pictures of infections were taken two or three genotypes of mango to outfit the significant learning model with the complete scope of signs for each ailment. The photos were then transformed by the methods for information increase to make the assistant dataset. These datasets were screened to focus in on model proficiency with entire leaf picture, yet a couple of pictures stood out from more altered leaves. The focal hypothesis was that the photos of altered leaves would overhaul model effectiveness to suitably see an infection as the educational assortment was more noticeable. Here beneath figure 3.2 show some informational index from 5 diverse class of the dataset.

Figure 3.2: Mango Leaves dataset with disease

3.3 Statistical Analysis

After implementing the deep learning classifier into the data set of mango leave disease the accuracy level is praise worthy. From the deep learning model we are using here two classifier one is DenseNet201 another one is InceptionV3. In both of these classifier we get the accuracy level of 98% and 96.67% respectively. Below table 3.1 show the confusion matrix for both of the two classifier of deep learning. Which consist of TP FP FN, TN. Where

TP= the quantity of cases effectively distinguished real class

FP= the quantity of cases inaccurately distinguished real class

TN= the quantity of cases effectively recognized negative classes

FN= the quantity of cases inaccurately distinguished negative classes

Table 3.1: Mango leaf disease Confusion Matrix

Method	Class	TP	FP	FN	TN
DenseNet201	Anthracnose	59	1	1	239
	Gall Machi	58	1	2	239
	Healthy Leaf	59	2	1	238
	Powdery Mildew	59	1	1	239
	Red Rust	59	1	1	239
InceptionV3	Anthracnose	56	1	4	239
	Gall Machi	57	2	3	238
	Healthy Leaf	59	3	1	237
	Powdery Mildew	59	4	1	237
	Red Rust	59	1	1	239

.3.4 Proposed Methodology

3.4.1 Image Acquisition

For implementing the deep learning model into the image net we are collecting a dataset of mango leaves. We are collecting mango leaves with disease. At first categorizing the diseases into 5 parts, 5 different leaves effected with disease are collected. These images are collected for training thee model again we are collecting the healthy leaves as well for. So that the model can easily making a distinguish between healthy laves and disease affected leaves. Almost 1000 pictures were used in this scenario for developing the model

3.4.2 Image Pre-processing

Prior to utilizing the image for division, some preprocessing of the photographs were done like Cropping-for cut-out the unimportant piece of the picture, Smoothing, improvement to change the covering and differentiation, Rotating, Resizing to get all of the photographs in a general development.

3.4.3 Model Description

The first layer of a CNN model is convolutional layer which is consider as an input image. The output of CNN can be denoted mathematically as follows

$$C_y^n = f\left(\sum_{x \in M_y} p_x^{n-1} * q_{xy}^n + r_y^n\right) \quad (1)$$

Where, C_y represents the set of output feature maps, M_y represents the set of input maps, qxy represents the kernel for convolution, ry represents the bias term. Below figure 3.3 depict the working procedure for CNN in this proposed work

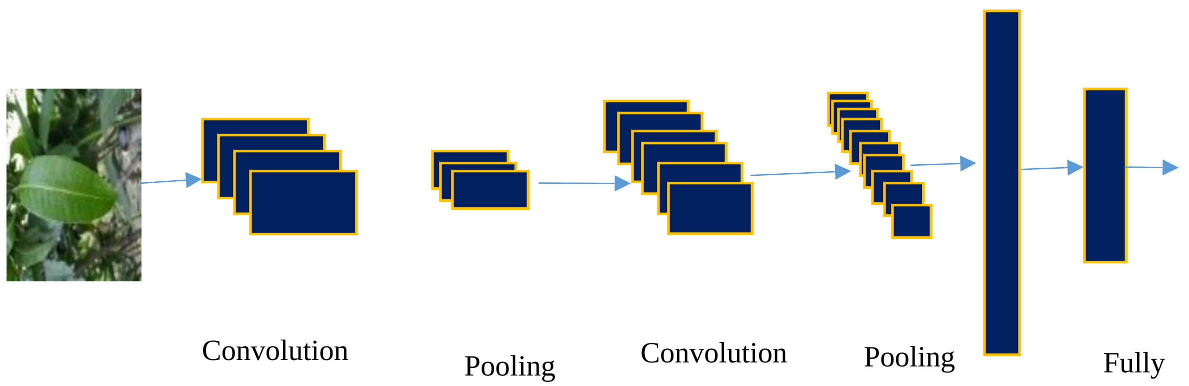

Figure 3.3 Working procedure of CNN in Mango disease detection

3.4.4 Model of Combinatorial Optimization for Deep Learning

The first intend to utilize Deep learning model to handle discrete smoothing out issues is to set up the Deep learning model to yield game plans directly from the Data model, as demonstrated in figure 3.4

Figure 3.4 Working procedure of Deep learning for a given problem

This methodology has been investigated into the model which is developed with deep learning. To handle the issue with profound learning present the pointer network wherein an encoder, to be specific a RNN, is utilized to parse all the hubs in the info diagram and delivers an encoding (a vector of initiations) for every one of them. Thereafter, a decoder, likewise a RNN, utilizes a consideration component comparable over the recently encoded hubs in the chart to create a likelihood conveyance over these hubs. Rehashing this deciphering step, it is feasible for the organization to yield a change over its data sources. This strategy makes it conceivable to utilize the organization over various information chart sizes. We are utilizing supervised learning for training purposes.

3.4.5 Configuration of Algorithms with developed model

Implementing only deep learning to handle the issue may not be the most appropriate methodology. All things being equal, again we can apply deep learning to give extra snippets of data to a combinatorial optimization calculation which is represented below figure 3.5. This image depict, Deep learning can give a parameterization of the calculation.

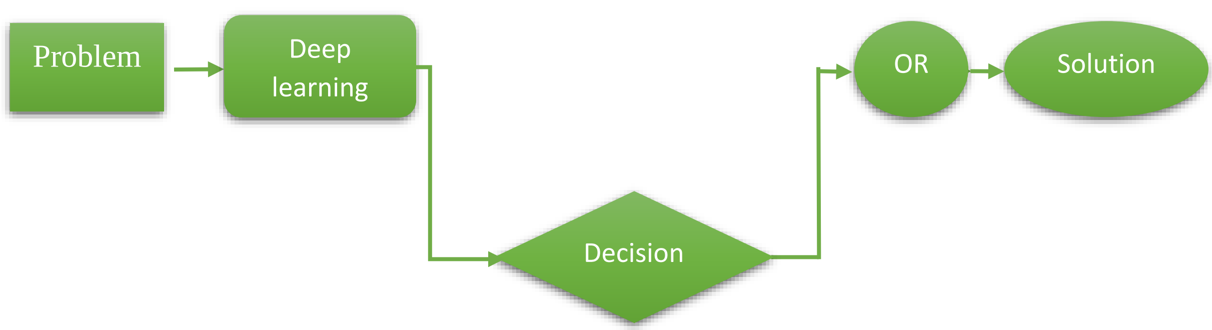

Figure 3.5 Deep learning model using for augmented research problem

Algorithm design, is an all-around considered region that catches the setting introduced here. Complex advancement calculations normally consist with large amount of boundaries left consistent at the time of advancement in deep learning which is termed as hyper-parameters. For example, this can be the forcefulness of the pre-tackling tasks normally constrained by a solitary boundary or the learning rate. Cautiously choosing their worth can drastically change the exhibition of the enhancement calculation. Subsequently, the calculation design local area began searching for great default boundaries. At that point great default boundaries for various group of comparable issue cases. From the Deep learning perspective, the previous is a consistent relapse, while the second is a portion steady closest neighbours relapse. The characteristic continuation was to get familiar with a relapse planning issue occurrences to calculation boundaries

3.5 Requirements for the Proposed Implementation

All the Requirements which are required for the proposed system are enlisted below.

- 8 GB Ram
- Anaconda
- Google colab
- At least 4 GB Memory
- Camera for capturing image

Chapter 4

Experimental Results and Discussion

4.1 Introduction

To get the unequivocal outcome, first the unrefined pictures were gathered and get from various bequests and shops. After pre-treatment of information, the fundamental organized dataset were ready. At long last the test picture is separated and the dataset utilizing Multi-class Support Vector Machine a complete result is displayed as the apparent class.

4.2 Experimental Results & Analysis

For test investigation of each model, we have used seven performance metrices. The accompanying conditions are utilized to assess the seven exhibition frameworks as Accuracy [8], Precision [9], F1 Score [10], Sensitivity [11], Specificity [12], FNR [13], FPR [14]

1. **Accuracy:** Accuracy can be formulated by below equation **:**

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \qquad \textbf{(2)}$$

2. **Sensitivity:** Sensitivity can be expressed as:

$$\textbf{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \qquad \textbf{(3)}$$

3. **Precision:** To assess the precision numerically, this can be expressed as:

$$\textbf{Precision}=\frac{TP}{TP+FP} \times 100\% \qquad \textbf{(4)}$$

4. **FPR:** FPR numerically can be expressed as:

$$\textbf{FPR:}\frac{FP}{FP+TN} \times 100\% \qquad \textbf{(5)}$$

5. **FNR:** FNR can be denoted as below :

$$\textbf{FNR:}\frac{FN}{FN+TP} \times \mathbf{100}\% \qquad \textbf{(6)}$$

From this performance matrices the measurement of the deep learning classifier is given beneath

Table 4.1. Class wise performance evaluation matrices for DenseNet201

DenseNet201							
Class	Accuracy	F1	Precision	Sensitivity	Specificity	FNR	FPR
Anthracnose	98.00%	98.31%	98.33%	98.33%	99.58%	1.67%	0.42%
Gall Machi		97.48%	98.30%	96.67%	99.58%	3.33%	0.42%
Healthy Leaf		97.52%	96.72%	98.33%	99.17%	1.67%	0.83%
Powdery Mildew		98.33%	98.33%	98.33%	99.58%	1.67%	0.42%
Red Rust		98.33%	98.33%	98.33%	99.58%	1.67%	0.42%

Table 4.1 shows the presentation assessment matrices for the DenseNet201 model for Class astute (Anthracnose, Gall Machi, Healthy Leaf, Powdery Mildew, and Red Rust). We find from table 2 that the precision is 98.00% for the ID of sicknesses of mango leaves. F1score, accuracy, sensitivity, explicitness, FNR, and FPR have likewise been estimated. The most noteworthy F1 score for Powdery Mildew, Red Rust, was 98.33%. The most noteworthy accuracy and sensivity, found for Anthracnose, Powdery Mildew, and Red Rust, is 98.33%. The most noteworthy particularity, noticed for Anthracnose, Gall Machi, Powdery Mildew, Red Rust, is 99.58%.The least FNR and FPR, found for Anthracnose, Powdery Mildew, Red Rust, is 1.67% and .042% too.

Again for the classifier InceptionV3 the evaluation result with all of the performance matrices is given below Table 4,2 shows the evaluation of InceptionV3 classifier with the performance matrices

Table 4.2. Class wise performance evaluation matrices for InceptionV3

InceptionV3							
Class	Accuracy	F1	Precision	Sensitivity	Specificity	FNR	FPR
Anthracnose	96.67%	95.73%	98.25%	93.33%	99.58%	6.67%	0.42%
Gall Machi		95.80%	96.61%	95.00%	99.17%	5.00%	0.83%
Healthy Leaf		96.72%	95.16%	98.33%	98.75%	1.67%	1.35%
Powdery Mildew		96.72%	95.16%	98.33%	98.75%	1.67%	1.25%
Red Rust		98.33%	98.33%	98.33%	99.58%	1.67%	0.42%

Table 4.2 shows the exhibition assessment networks for the InceptionV3 model for Class shrewd. We find from table 4 that the precision is 96.67% for the ID of infections of mango leaves utilizing InceptionV3 model. F1score, precision, affectability, explicitness, FNR, and FPR have likewise been estimated. The most noteworthy F1 score for Red Rust, was 98.33%. The most elevated accuracy, found for Red Rust, is 98.33%.The most elevated affectability, noticed for Healthy Leaf, Powdery Mildew, Red Rust, is 98.33%. The most noteworthy particularity, noticed for Anthracnose, and Red Rust, is 99.58%.The least FNR, found for Healthy Leaf, Powdery Mildew, and Red Rust, is 1.67%. For Anthracnose the lower FPR is 0.42%.

4.2.1 Analysis for Combinatorial Optimization for the deep learning model

To sum up the setting of the past segment to its maximum capacity, one can fabricate Combinatorial Optimization calculations that over and again call a Deep learning model all through their Execution. An expert calculation assuage the undeniable structure of level while habitually call a Deep learning model to aid level of lower choices. The critical distinction between this methodology and the models examined in the past segment is that a similar Deep learning model is utilized by the Combinatorial Optimization calculation for settling on similar sort of choices various occasions in the request of the quantity of cycles of the calculation. As in the past area, nothing keeps one from applying extra strides previously or after such a calculation. Below figure 4.2 illustrate the analysis.

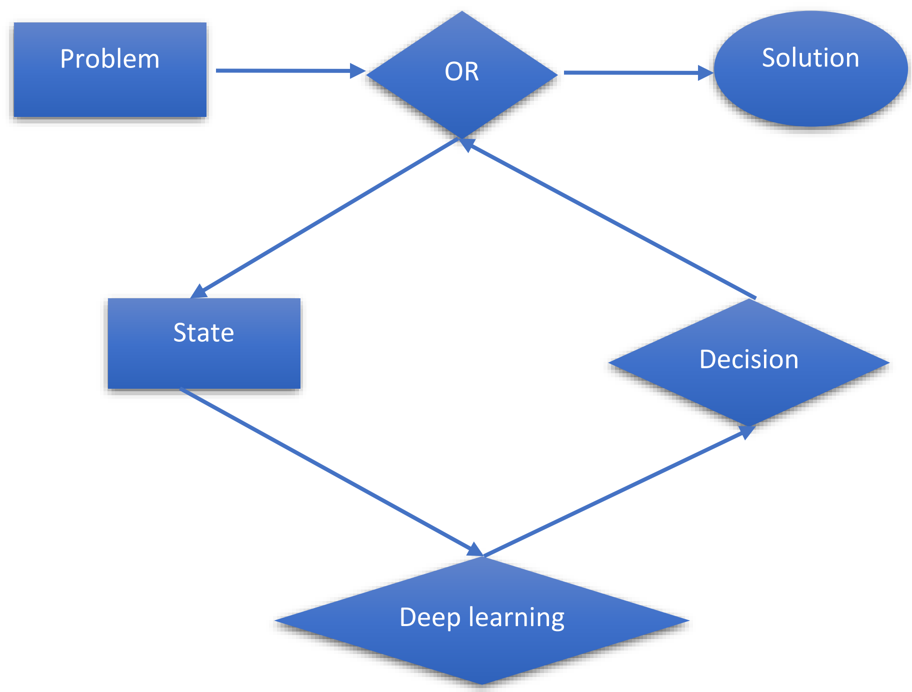

Figure 4.2 Analysis of Combinatorial Optimization problem over Deep learning model

The combinatorial enhancement computation on and on requests a similar Deep learning model to choose. The Deep learning model takes as data the current state of the computation, which may consolidate the troublesome definition.

4.2.2 Problem formulation for Deep learning over Combinatorial Optimization

For the definition from the start we portray I to be a lot of issue factor, and P is an appropriation of likelihood over I. These are the issues that we really think about it about, weighted by a probability spread, reflecting the path that, in a functional application, not all issues are as reasonable. Before long, I or P are far off, anyway we can see a couple of models from P, as roused in the show with the Montreal movement association. For a lot of computations A, let $M: I \times A \rightarrow R$ be an extent of the introduction of an estimation on an issue case (lower is better). This could be the objective regard of the best game plan found, yet could similarly join segments from optimality limits, nonappearance of results, running events, and resource use. To break down a1, a2 ∈ A, a deep learning specialist would think about $(\mathrm{Ei} \sim \mathrm{P}\ \mathrm{m}(\mathrm{i}, \mathrm{a1}))$ and $(\mathrm{Ei} \sim \mathrm{P}\ \mathrm{m}(\mathrm{i}, \mathrm{a2}))$or proportionally. So the equation for the formulation is given below

$$\min_{a \in \{a1, a2\}} \mathrm{Ei} \sim \mathrm{P}\ \mathrm{m}(\mathrm{i}, \mathrm{a}) \tag{7}$$

Though the equation gives the result proportionally but the measurement of the quantities is not traceable, for this reason we need to use the train data set for the measurement, this dataset belongs to the model of deep learning which we can be defined as independent instances sample from P

$$\min_{a \in \{a1, a2\}} \sum_{i \in train\ data} \frac{1}{train\ data}\ m(i, a) \tag{8}$$

For any type of problem at first we are just collecting the data set and compare the expected outcome like running time, average running time, error value. This is the more specific learning problem this could be happened for every possible dataset for every I and for every P and the different measurement should be computed as m. This is the most explainable learning problem which could be express through the below equation 9

$$\min_{a \in A} \mathrm{Ei} \sim \mathrm{P}\ \mathrm{m}(\mathrm{i}, \mathrm{a}) \tag{9}$$

Maybe than differentiating between two algorithms, we may consider among an uncountable, potentially non-parametric, space of calculations. However, handling this issue is troublesome. From one viewpoint, the show measure m is consistently not differentiable and without shut design enunciation.

4.2.2 The mathematical part of the combinatorial part

According to the formula

We have 500 images for per classes.

We have 5 classes

and using the 80% for training purposes and 20% for testing purposes.

So, we have 2000 image in total so the train and test distribution is like

Training data set = 2000

Testing data set = 500

So, the formula is

Accuracy = P*(1/train data) *I*a = 78.4*(1/2000) *5*5 = .98 [For DenseNet201]

Where we can find that,

I= bunch of problem factor = 5 [we have 5 problem factors]

P = probability over distribution

A = total assets which we got from the data set

(i) If we explain the factors then we get that,

I= bunch of problem factor = 5 [we have 5 problem factors]

Because for this research work, we are using mango leaf data set and categorize that into 5 classes.

- Anthracnose,
- Gall Machi,
- Powdery Mildew,
- Red Rust
- Healthy leaf

P = probability over distribution .

(ii) **This explains what is the possible distribution percentages of the data . We could calculate the procedure .**

- Anthracnose = 70
- Gall Machi = 61
- Powdery Mildew = 86
- Red Rust = 95
- Healthy leaf = 13 [using the image of 13 different healthy leaves based on their shapes]

So, if we making the average then average = (95+86+61+70)/4 = 78. We could count is as 78% raw data is provided or distributed in each classes based on quantity of each data image amount. And the healthy leaf is 13 which is almost 4 % of other data set this could be the total data of 4 class is 95+86+61+70 = 312 so the percentage is 312 * .04 = 12.88 [total healthy leaf is 13] , we count is this way because we need to compare healthy leaves to each of the classes .In Total we have 78.4% data distributed for each classes

(iii) A = total assets which we got from the data set

In every class we are using 5 different images for each disease based on their positions on leaves.

This is considered the assets which defines the unique value of the data set

4.3 Discussion

In the various models we have overviewed, deep learning is utilized in both definite also, heuristic systems. Getting the yield of a deep learning model to regard progressed sorts of limitations is a hard errand. To construct definite calculations with deep learning parts, it is important to apply the deep learning where all potential choices are legitimate. Utilizing just ML as overviewed can't give any optimality ensure, and just frail plausibility ensures. Be that as it may, applying deep learning to choose or parameterize a Combinatorial Optimization calculation will keep precision if every single imaginable decision that deep learning separate lead to finish calculations. At last, on account of rehashed communications among deep learning and CO, all potential choices should be legitimate.

Chapter 5

Conclusion of the proposed work

5.1 Introduction

In this work I'm trying to create a fusion of deep learning work in the texture of Combinatorial Optimization approaches. The summary of my whole work is given below -

- **First Step:**

  a) Data collection

  b) Data pre-processing

  c) Feature extraction

- **Second Step:**

  Provide image as input of the diseases

- **Third Step:**

  Justify the proposed method by taking the user input

- **Fourth Step:**

  Classification result for particular Disease among various algorithm

- **Fifth Step:**

  Applying combinatorial optimization into the developed model.

- **Final Step :**

  Find the best approaches applying Combinatorial Optimization

5.2 Conclusions

In this proposed work we are discussing the way deep learning can be utilized for fabricating combinatorial Optimization algorithm which may halfway scholarly. This work proposed a strategy which outline a pantomime learning alone can be significant if the course of action learned is generally speedier to figure than the first gave by a trained professional, for the present circumstance a combinatorial upgrade computation. On the inverse, models arranged with an honor sign can beat current courses of action, given adequate getting ready and a directed instatement. Setting up a methodology that summarizes to disguised issues is a test, this is the reason we figure learning should occur on a scattering minimal enough that the system could totally abuse the plan of the issue and give better outcomes. We acknowledge beginning to end profound learning approaches to manage combinatorial smoothing out can be improved by using profound learning in blend in with current combinatorial smoothing out estimations to benefit by the speculative confirmations and state of the art computations successfully available.

5.3 Implication for Further Study

We are briefly discussing into the section that how deep learning is used to directly find the output from the solution to an optimized problem. Learning the arrangement, it would be more accurate to say that the calculation is learning a heuristic. As of now over and over noticed, the learned algorithm doesn't give any assurance regarding optimality, yet it is significantly more important that practicality isn't ensured by the same token. In reality, we don't have a clue how far the yield of the heuristic is from the ideal arrangement, or in the event that which again regards limitations for some issues. Which is situation for each heuristic and the problem can be moderated after utilizing the heuristic inside with accurate improvement algorithm. Finding the optimal solution is not an easy task but it becomes more difficult when it comes with deep learning especially by using neural network. Neural network must be designed carefully so that it could be able to give the better solution in the terms of Combinatorial Optimization problems.

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Appendices

Appendix A: Research Reflection

The motivation behind this Appendix is to give a prologue to Research refection. The individual research venture was a difficult and agreeable experience run of the mill of the course all in all. I have had little exposer to gather work at university. In this way, it was a decent change to be a piece of a successful and dynamic.

The experience instructed us that arranging and making reactions takes a more drawn out time in groups than all alone. The broad exertion required was eventually something to be thankful for. I continually creating and refining the thoughts. I needed to go to towns and ranches to collect the pictures, and obviously that was very getting a charge out of and furthermore trying for me. I appreciated a lot conversing with the farmers who helped us a lot. This examination results would push them to their future development definitely.

Appendix B: Related Issues

Gathering pictures from this sort of urban territory like Dhaka was troublesome. I needed to go to villages and markets to catch the ailment influenced orange and orange leaves pictures. I needed to converse with the ranchers some time to let them comprehend the issue and significance of the investigation. They were well disposed however to support me.

I needed to adapt such a significant number of new calculations and procedures to actualize our thoughts and research work to be compelling. Variety of the picture foundations and nature of the pictures were trying to adjust and decrease the adjustments in results hereby.

riented_prediction_for_combinatorial_optimization_problem...

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