Real Time Rice Field Weeds Detection Using Machine Learning in the Context of Bangladesh

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A Thesis report submitted in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering

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Declaration

We, Md. Kamrul, Sayam Hossain Bhuiyan Aumy, Mehedi Hasan Mridha, Imam Hossain Sajeeb and Subir hereby, declare that the work presented in this capstone project report is the outcome of the investigation performed by us under the supervision of honorable Dr. Md Sawkat Ali, assistant professor of department of Computer Science and Engineering, East West University. We also declare that no part of this project has been or is being submitted elsewhere for the award of any degree or diploma, except for publication.

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Letter of Acceptance

The thesis "Real Time Rice Field Weeds Detection Using Machine Learning in the Context of Bangladesh" is submitted by Md. Kamrul, Sayam Hossain Bhuiyan Aumy, Mehedi Hasan Mridha, Imam Hossain Sajeeb and Subir to the Department of Computer Science and Engineering, East West University, Dhaka, Bangladesh is accepted for the partial fulfillment of the requirement for the degree of Bachelor of Science in Computer Science and Engineering on (Date/Month/Year).

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Abstract

The current world population has reached 7.9 billion and is increasing daily. Among all the countries in the world, the population of Bangladesh is equal to 2.11% of the total population of the world and it ranks 8th in the list of countries by population. Ensuring food security for this large population is now a major challenge. There is no alternative to increasing food production to meet this challenge. According to the FAO report, Bangladesh was the third largest rice producing country in the world, producing 37.8 million tons of rice in 2021. But rice production in Bangladesh is significantly being disrupted by natural and man-made factors such as droughts, floods, harmful insects, weeds, carbon emissions etc. Among them, weeds cause serious problems in rice cultivation. Weed management with manual labor requires 98 man-hours per hectare. There is a great opportunity to save labor input and cost up to 78% for weed control using mechanical methods. So, the authors of this paper used machine learning methods to detect the weeds of rice field. 4 prominent algorithms- CNN, VGG16, Inception V3 and DenseNet are used to design a system and all of the algorithms showed high accuracy to detect the weeds. The algorithms are trained and tested with a unique dataset collected by the same authors. Weed detection accuracy was 87% for the CNN model, 96% for the VGG16 model, 93% for the Inception V3 model, and 98% for the DenseNet model. Using this system, the authors developed an android mobile application that can detect weeds in real time with high efficiency.

Acknowledgement

As it is true for everyone, we have also arrived at this point of achieving a goal in our life through various interactions with and help from other people. However, written words are often elusive and harbor diverse interpretations even in one's mother language. Therefore, we would not like to make efforts to find the best words to express my thankfulness other than simply listing those people who have contributed to this thesis itself in an essential way. This work was carried out in the Department of Computer Science and Engineering at East West University, Bangladesh.

First of all, we would like to express my deepest gratitude to the almighty for His blessings on us. Next, our special thanks go to our supervisor, Dr. Md Sawkat Ali, who gave us this opportunity, initiated us into the field of "Real Time Rice Field Weeds Detection Using Machine Learning in the Context of Bangladesh", and without whom this work would not have been possible. His encouragements, visionaries and thoughtful comments and suggestions, unforgettable support at every stage of our B.Sc. study were simply appreciating and essential. His ability to muddle us enough to finally answer our own question correctly is something valuable what we have learned and we would try to emulate, if ever we get the opportunity.

There are numerous other people too who have shown us their constant support and friendship in various ways, directly or indirectly related to our academic life. We will remember them in our heart and hope to find a more appropriate place to acknowledge them in the future.

Md. Kamrul
February 2023

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Chapter 1

Introduction

1.1 Background

The current world population has reached 7.9 billion. Ensuring food safety for this large population is now a major challenge. The average person in the world consumes approximately 675 kg of food per year, or 1.85 kg of food per day. The most consumed food in the world is Milk (79.3 kg per person), which is equivalent to 12% of all food consumed in the world, followed by Rice (78.4 kg per person), Wheat (67 kg per person) [1]. To supply this huge amount of food, food production has to increase a lot. So, there is no substitute for agriculture to ensure food safety for today's growing world population.

According to the OECD-FAO Agricultural Outlook 2020-2029 report, 81% of world milk production is cow milk, 15% buffalo milk and 4% goat, sheep and camel milk. Total milk production of all types increased by 1.3% in 2019, reaching about 852 million tons. According to FAO data, this production amounted to 843 million tons in 2018. India is the world's largest milk producer, making up 22 percent of global production in milk of all types [2].

Global rice consumption has increased slightly in the last few years. In the year 2021/2022, about 509.87 million metric tons of rice was consumed globally, up from 483.817 million metric tons in the year 2016/2017.

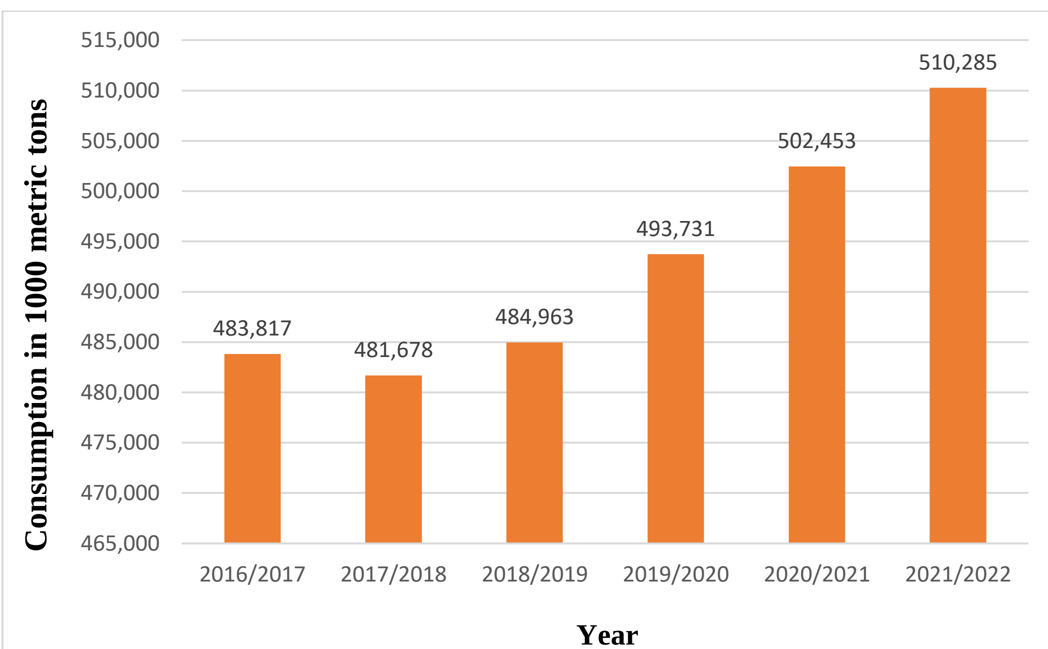

Figure- 01: Total rice consumption worldwide from 2016/2017 to 2021/2022

In 2020, China produced about 211.86 million metric tons of paddy rice, making that country the top producer of paddy rice worldwide. India had the largest harvest area of rice in the 2019/2020 crop year, at 44 million hectares, while China harvested 30.8 million hectares of rice in that year. In addition to having the largest harvest area of rice, India also was the top exporter of rice in the 2021/2022 fiscal year. During that time period, India exported 18.75 million metric tons of rice [3].

In the 2019/2020 marketing year, global production of wheat was over 765 million metric tons. This is an increase of more than 30 million tons compared to the previous marketing year. China is the world's largest wheat producer, producing over 2.4 billion tons of wheat in the past two decades, accounting for about 17% of total production from 2000-2020. The second largest wheat producing country - India produced 12.5% of the world's wheat in the last two decades [4] [5].

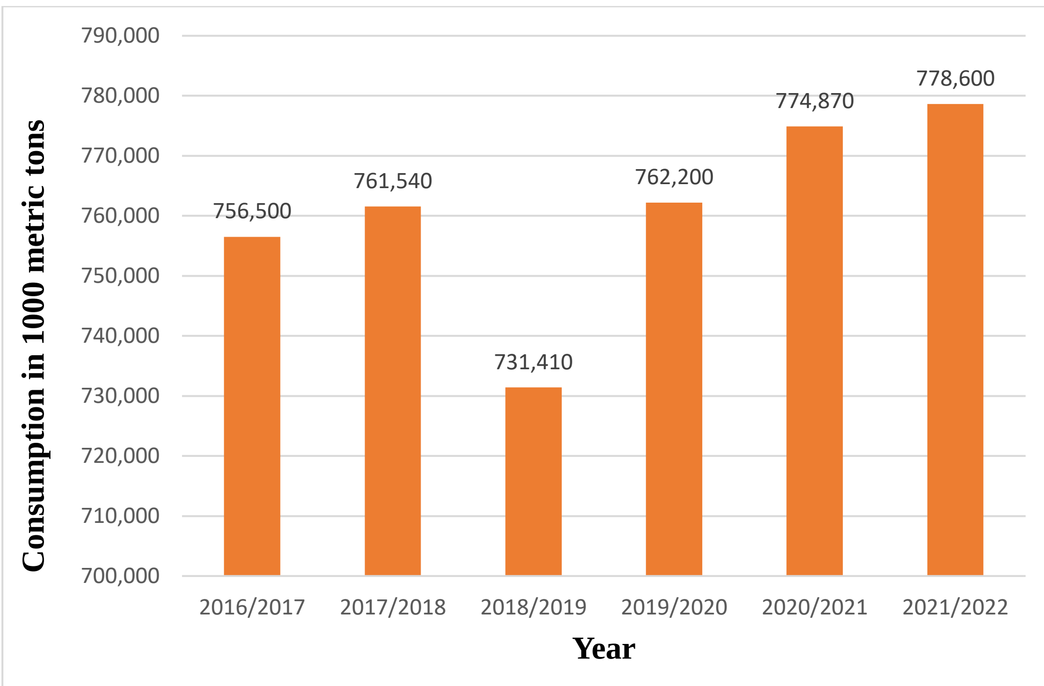

Figure- 02: Total wheat consumption worldwide from 2016/2017 to 2021/2022

But global food production is significantly disrupted by natural and man-made factors such as droughts, floods, wildfires, harmful insects, weeds, radioactivity, carbon emissions etc. Among them, weeds cause serious problems in crop cultivation.

1.2 Problems

Rice fields have sufficient water to grow weeds in abundance, which reduces crop yields drastically. Usually, yield loss is between 15-20%, but in severe cases, yield loss can exceed 50% depending on weed species and severity. These include grasses, sedges, and broadleaf weeds that reduce rice crop yields by up to 76% [6].

Weeds are plants that are undesirable, persistent, damaging, and interfere with the growth of other crop plants thus affecting human activities, agriculture, natural processes and the economy of the country [7].

1.2.1 Classification of Weeds

Weed can be classified into three categories: annual, biennial and perennial.

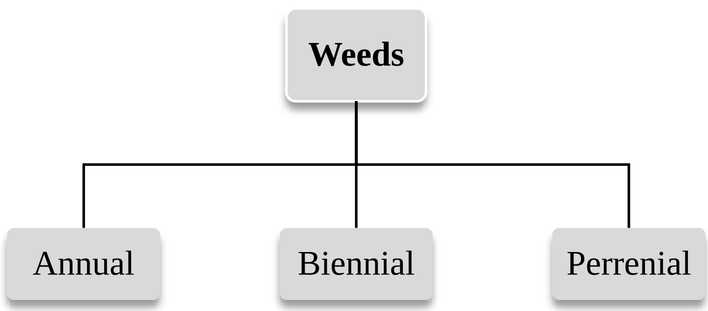

Figure- 03: Weed classification

Some examples of these weeds are as follows:

Table- 1: Some Example of weeds according to classification

Annual	Amaranth, Common lambsquarters, Milk thistle, Ragweed
Biennial	Burdock, Wild carrot
Perennial	Bermuda grass, Broadleaf plantain, Cogongrass, Creeping charlie, Goldenrod, Sorrel, Yellow nutsedge

Weeds can hinder the proper development of a crop because they:

1. Compete for light, moisture and nutrients which affect the quality and quantity of produce.
2. They give shelter to pests and diseases.
3. Have toxic properties that can cause health problems for humans and animals.
4. Pollute water resources and hamper irrigation.
5. Adversely affect natural ecosystems.

Crop production loss due to weeds depends on various factors such as emergence time of weed, weed density, type of weed, environment, crop etc. If weed growth is not controlled, it can cause 100% crop loss. The overall annual cost of weed control to Australian crop growers is estimated at AUD 3.3 billion. At the national level crop yield losses due to weeds amounted to 2.7 million tons of grain. This cost is very high in India. Weeds cost India's agricultural production USD 11 billion a year. Yield losses due to weeds are estimated at 19% in wheat, 25% in maize, 31% in soybean and 36% in peanut. In the United States, annual costs of crop production due to weeds are estimated at USD 33 billion [8]. Various studies suggest that weeds, which have long taken advantage of cropland fertility, evolved in response to the Neolithic Agricultural Revolution around 12,000 years ago. However, researchers found evidence of "proto-weeds" behaving similarly at Ohalo II, a 23,000-year-old archaeological site in Israel [9].

Proper weed control is a challenge in crop production today.

Bangladesh is no exception in this regard.

1.2.2 Impact of Weeds on Crop Production in Bangladesh

Agriculture is the largest employment sector in Bangladesh. It is contributing up to 12% to the GDP of Bangladesh in 2020 and is providing 37.75% of employment opportunities [10] [11]. The sector has a huge role to play in key macroeconomic goals such as employment generation, human resource development, poverty alleviation, food security, and other economic and social forces. Agriculture has played a significant role in reducing poverty in Bangladesh from 48.9% in 2000 to 31.5% by 2010 with more than 87% of the rural population receiving some income from their agricultural activities [12].

The major food crop of Bangladesh is rice, which consumes about 75% of the agricultural land. Bangladesh is the fourth largest rice producing country in the world. The annual demand for rice is about 37 million tons [13]. According to the FAO report, Bangladesh was the third largest rice producing country in the world, producing 37.4 million tons in 2020 and 37.8 million tons in 2021 [14]. The United States Department of Agriculture (USDA) estimates that Bangladesh produced 35.8 million tons of rice in 2020 [13]. But every year rice production is disrupted due to various reasons. Drought, floods, salinity and insects and weeds are major constraints to rice production in Bangladesh. Among them weeds are one of the major bio- constraints of rice in Bangladesh and are a significant factor in reducing its yield.

The major weeds responsible for disrupting rice production are as follows:

1. ***Paspalum scrobiculatum***

Table- 2: Description of *Paspalum scrobiculatum*

Common names	Scrobic, kodo millet, koda millet, creeping paspalum, rice grass Paspalum[15].
Description	*Paspalum scrobiculatum* is a vigorous, tufted (up to 60 cm diameter) and slender perennial grass. Paspalum scrobiculatum var. scrobiculatum is

	grown in India as an important crop It grows wild in the west of Africa. In Bangladesh it grows as a weed in rice fields. Many farmers do not mind it, as it can be harvested as an alternative crop if their primary crop fails. It grows to a height of 0.3-1 m. The roots are rather shallow and the stems are ascending, branched and somewhat succulent. Leaf blades are 15-40 cm long, 5-12 mm wide, pale green. Leaf sheaths and leaves are glabrous. The inflorescence is a panicle, generally consisting of 3-4 racemes, 4-9 cm long. The spikelets are arranged in two or three rows. Seeds are ellipsoidal, 2 mm long, 1.5 mm wide and light brown colored[16].
Scientific classification	**Kingdom**: Plantae **Phylum**: Tracheophyta **Class**: Liliopsida **Order**: Poales **Family**: Poaceae **Genus**: Paspalum **Species**: Paspalum scrobiculatum L [15]
Image	

2. ***Ipomoea aquatic***

Table- 3: Description of *Ipomoea aquatic*

Common names	Water spinach, Swamp morning glory, Morning glory, Kalmi-sak, Sarnali [17].
Description	*Ipomoea aquatic* is widely known as 'water spinach' which is a semi-aquatic- tropical plant. It grows abundantly near water reservoir. Its stems are 2–3 metres (7–10 ft) or longer, rooting at the nodes, and they are hollow and can float. The leaves vary from typically sagittate (arrow head-shaped) to lanceolate, 5–15 cm (2–6 in) long and 2–8 cm (0.8–3 in) broad. The flowers are trumpet-shaped, 3–5 cm (1–2 in) in diameter, and usually white in colour with a mauve centre [18].

Scientific classification	**Kingdom**:	Plantae
	Phylum:	Tracheophyta
	Class:	Magnoliopsida
	Order:	Solanales
	Family:	Convolvulaceae
	Genus:	Ipomoea
	Species:	Ipomoea aquatica Forssk. [17]
Image		

3. ***Cyperus ochraceus***

Table- 4: Description of *Cyperus iria*

Common names	Umbrella sedge, rice flat sedge, barachucha [19].
Description	*Cyperus iria* commonly known as 'ricefield flatsedge' is an annual sedge in rice fields. It is a lowland rice weed found in 22 countries around the world. It spreads fast just along with the crop seeding time. A fully grown plant can contain around 5000 seeds which sheds within one month and establish second generation colony within the same crop season. Within one crop cycle this weed complete three to four cycles and fight for nutrition, minerals, irrigation etc with the actual crop [20]. Its seeds are germinated within 7.2 days on average. Approximate germination rate is between 65 % to 100%. If germination time of weed aligns with the germination time of crop then there is high possibility that crop will germinate poor that will cost damage and production quality and quantity both will be affected [21].
Scientific classification	**Kingdom**: Plantae **Phylum**: Viridiplantae **Class**: Tracheophyta **Order**: Poales **Family**: Cyperaceae **Genus**: Cyperus L **Species**: Cyperus iria L. [19]

Image	

4. ***Centella asiatica***

Table- 5: Description of *Centella asiatica*

Common names	Indian pennywort, marsh pennywort, asian pennywort, gotu kola [22].
Description	*Centella asiatica* is well known in Indian subcontinent in the name of 'Gotu Kola', which is being used as a natural medicine unfortunately this grows as a weed in rice fields. This weed expands by creating clusters made up of creeping stems. It spreads colonies by stems as well as with seeds carried by water and contaminated soil [23]. This is often used as natural remedies for various deceases but unexpected hence regarded as weed id rice field and other plantation crops. It is regarded as an invasive weed [24].
Scientific classification	**Kingdom**: Plantae **Phylum**: Tracheophyta **Class**: Magnoliopsida **Order**: Apiales **Family**: Apiaceae **Genus**: Centella L **Species**: Centella asiatica L. [22]
Image	

5. *Panicum repens*

Table- 6: Description of *Panicum repens*

Common names	Torpedograss, creeping panic, panic rampant, couch panicum, wainaku grass, quack grass, dog-tooth grass, and bullet grass [25].
Description	*Panicum repens* commonly known as 'torpedograss' is grass species widely found in rice fields. It is classified as a Noxious weed which cost serious damage to crops. It grows quickly nearly 1.3 cm per day which is alarming for rice fields. It can grow in all situations like muddy, watery even in draught full atmosphere. Primarily is spreads though rhizomes which also produce tillers. When rhizomes are broken or dropped of the germinate new shoots and soon spreads colony. It has little positive sight that it has high soil binding capacity due to dense creeping stems and thus used for stabilizing soil in shorelines, river banks [25].
Scientific classification	**Kingdom**: Plantae **Phylum**: Tracheophyta **Class**: Magnoliopsida **Order**: Poales **Family**: Poaceae **Genus**: Panicum L **Species**: Panicum repens L. [26]
Image	

6. *Marsilea minuta*

Table- 7: Description of *Marsilea minuta*

Common names	Gelid waterklawer, small water clover, airy pepperwort, pepperwort etc [27].
Description	*Marsilea minuta* is a species of aquatic fern in the Marsileaceae family. In water the plant appears creeping and spreading, while on land it looks like a cushion. It is usually a perennial plant but sometimes occurs as an annual. It is a tenagophyte, with juveniles submerged in water and adults usually terrestrial. It can grow in freshwater or brackish water on clayey or

	sandy soils up to 1,950 meters above sea level. These plants can develop into large colonies and become weeds [27].
Scientific Classification	**Kingdom**: Plantae **Phylum**: Tracheophyta **Class**: Polypodiopsida **Order**: Salviniales **Family**: Marsileaceae **Genus**: Marsilea **Species**: Marsilea minuta L [28]
Image	

7. ***Alternanthera philoxeroides***

Table- 8: Description of *Alternanthera philoxeroides*

Common names	Alligator weed, Pig weed, Alligator grass [29].
Description	*Alternanthera phylloxeroids* is a highly branched, amphibious plant, often growing densely in very wet or flooded areas. Its hollow stem grows to a length of at least 1 m. These hollow stems are striated and root at their lower nodes and usually branch from the basal part. The leaves are simple, obtuse, opposite, leaflets oblong, narrowly ovate or linear, narrowed at base, obtuse [29].
Scientific classification	**Kingdom**: Plantae **Phylum**: Tracheophyta **Class**: Magnoliopsida **Order**: Caryophyllales **Family**: Amaranthaceae **Genus**: Alternanthera **Species**: Alternanthera philoxeroides (Mart.) Griseb. [29]

Image	

8. ***Synedrella nodiflora***

Table- 9: Description of *Synedrella nodiflora*

Common names	Nodeweed, Cinderella weed [30].
Description	Synedrella nodiflora is an erect, branched grass which is usually 40 to 90 cm high. The 5 to 10 cm long leaves are simple and oppositely arranged and light green in color containing 3 basal veins. The margin of the leaf blade is serrated or almost full and the underneath is hairy. The flowers are small and yellow and they are grouped into small heads at the base of terminal leaves [31].
Scientific classification	**Kingdom**: Plantae **Phylum**: Tracheophyta **Class**: Magnoliopsida **Order**: Asterales **Family**: Asteraceae **Genus**: Synedrella **Species**: Synedrella nodiflora (L.) Gaertn [31]
Image	

9. *Fimbristylis littoralis*

Table- 10: Description of *Fimbristylis littoralis*

Common names	Lesser fimbry or lesser fimbristylis. [32]
Description	The annual grass-like or herb sedge has a tufted habit and typically grows to a height of 0.05 to 0.7 meters. It has slender culms slender with a length of 40 to 60 cm tall, four or five-angled, and often flattened. The leaves are up to a length of 40 cm and are 1.5 to 2.5 mm wide. Basal leaves that are about half the length of the culm, are threadlike, and stiff. It is native to many countries in Asia, and Africa. It is a problematic plant in rice fields all around the world. It is a weed of open slopes, muddy places, grasslands, and paddy fields. [33]
Scientific classification	**Kingdom**: Plantae **Phylum**: Tracheophyta **Class**: Liliopsida **Order**: Poales **Family**: Cyperaceae **Genus**: Fimbristylis **Species**: Fimbristylis littoralis Gaudich. [34]
Image	

10. *Commelina benghalensis*

Table- 11: Description of *Commelina benghalensis*

Common names	Tropical spiderwort, Dayflower, Dholpata, Kanchira, Kanai bashi [35].
Description	*Commelina benghalensis* is a highly branched plant with aerial and underground stems. The roots grow at the nodes of aerial stems which are thickened. The leaves are arranged alternately along the stem, more or less hairy on both sides and have large reddish shining hairs at the base and edge of the sheath. They also have parallel veins. The flowers are pale blue to white in color. They are covered in a small triangular leaf structure with the

	edges fused towards the back and the sides sparsely covered with white hairs [35].
Scientific classification	**Kingdom**: Plantae **Phylum**: Tracheophyta **Class**: Liliopsida **Order**: Commelinales **Family**: Commelinaceae **Genus**: Commelina **Species**: Commelina benghalensis L. [35]
Image	

11. ***Pteris vittata***

Table- 12: Description of *Pteris vittata*

Common names	Chinese brake, Chinese ladder brake, Ladder brake [36].
Description	*Pteris vittata* grows in crop field as a weed. It is endemic and widespread in the Paleotropics: from the east, found in the southern tropics and southern Africa. Although it grows abundantly in cropland, it is sometimes cultivated [36].
Scientific classification	**Kingdom**: Plantae **Phylum**: Tracheophyta **Class**: Polypodiopsida **Order**: Polypodiales **Family**: Pteridaceae **Genus**: Pteris **Species**: Pteris vittata [36].

Image	

1.2.3 Weed Detection

A prerequisite for weed management is detecting the right weeds and separating the right weeds from the crop. And the farmer has to do this work properly and for this they need proper education. Usually they get this education from their ancestors. In Bangladesh, various organizations including the Department of Agricultural Extension and agricultural universities and research institutes provide excellent information on important weed species and color plates to help farmers identify the correct weeds [37].

In this age of technology, weed detection is also possible with the help of information technology. In this regard, technicians take the most help from Machine Learning (ML). Apart from that, the use of IoT is also observed. Some prominent techniques of these are:

Machine Learning: Some ML methods have shown promising results in weed detection:

1. <u>Machine Vision</u>: Using Machine vision with appropriate image processing algorithms 98.7% weeds are detected.
2. <u>SVM</u>: Support Vector Machine or SVM can identify 95.7% weed using lighting on the target by using an active light source
3. <u>Image Processing</u>: 92.7% accuracy has been achieved using many technological, mechanical equipment. In the other hand 96% accuracy is achieved using RF.
4. <u>Neural Network</u>: Neural Network showed 99% accuracy.

Internet of Things (IoT):

With the help of IoT, image processing and CNN 85% weeds can be detected.

Weed detection with the help of various information technology will be described detailed with proper citation in Related Work part of this paper.

1.2.4 Traditional Weed Controlling

Weed controlling is very important to produce the desired crop. The farmers are managing this work in various ways for many years. Some of the prominent methods among them are mentioned below:

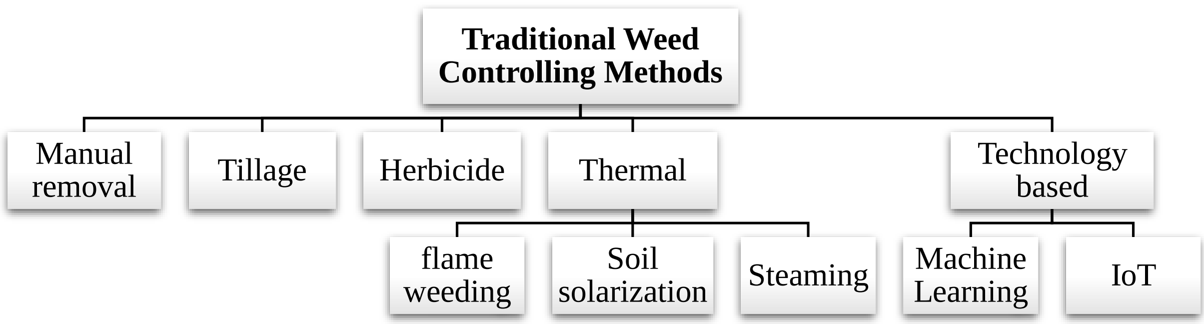

Figure- 04: Some Prominent weed controlling methods

Manual removal

Pulling weeds is an effective method to prevent the spread of weeds. This method is also known as manual removal. Many farmers still pull weeds from the soil by hand and eradicate them. There are two types of pulling-weed methods- hand-pulling and pulling-using-tool. Hand-pulling is useful for weed control in small areas as it is easy to implement. This requires removing the roots without disturbing the soil too much. On the other hand, in the pulling-using-tool method, the weed stem is properly grasped with a tool and its roots are removed.

Manual removal method is useful in areas where herbicides cannot be applied. This method is quite time consuming but has very low ecological impact. Moreover, it requires a lot of manpower and the production cost of the crop increases significantly.

Tillage

Soil turning or 'tilling' is used to protect agricultural crops from weeds. This method is usually applied where the soil is already seriously affected. 'Tilling' is done when the soil is dry and before the weed seeds germinate.

Thermal

Some thermal methods are also used for weed control.

Flame weeding uses a flash of flame a few centimeters/inches away from the weeds to destroy the plants' cell rather than burn the plant them. This method is the most widely used thermal weed controlling method worldwide, especially in western Europe for organic farming. The goal of flame weeding is not necessarily to burn the plant, but to destroy the protein in the weed. In the early 1940s, flame weeding's first large-scale agricultural application to control weeds in cotton production began in the United States. Initially liquid fuels such as kerosene and oil were used but later this was replaced by LPG (liquefied petroleum gas, mainly propane and butane). For commercial purpose, the mixture of propane and butane is used and propane flame can generate temperature up to 1900°C. It has some disadvantages- it needs high cost for fuel, labor and equipment [38].

Soil- solarization or Solar Heating (SH) is a method of increasing soil temperature until weeds are killed. Soil- solarization helps release nutrients trapped in the soil while killing weeds without the use of chemicals. Soil- solarization is usually done by covering the earth with black plastic to trap solar radiation and the temperature of upper layer of soil reach 40°C - 55°C. This should apply in crop free land. This method can affect the biological, physical and chemical composition of the soil which can reduce the growth of other plants [38].

Steaming is a weed controlling method where hot steam is used to destroy the weeds where herbicides cannot be used with less effort. Mobile soil steaming is used commercially in grown crop beds. especially in short-term fields, such as salad crops where the need for soil-borne pathogen control is immense. depending on the steaming time, Steam is applied over the entire grain area and 50-100 mm below the soil. This leads to a long-term and effective weed control, causing high mortality of weed seeds. Although this is a very effective control method, it uses a large amount of fossil fuel-diesel. Moreover, it affects several essential soil organisms and requires a long time for soil recovery [38].

Table- 13: Some popular thermal methods for traditional weed controlling

Author	Problem Definition	Used Technology	Findings from paper	Limitations	Reduction rate
Upadhyaya and Blackshaw [38]	Non-chemical Weed Management	LD_{95} Flame	Flaming kills plants by breaking down plant cells and leading to tissue desiccation	High cost of labor, fuel and equipment	95%
		ED_{95} Flame	Flaming kills plants by breaking down plant cells and leading to tissue desiccation	High cost of labor, fuel and equipment	95%
		Propane Flame	Flaming kills plants by breaking down plant cells and leading to tissue desiccation	High cost of labor, fuel and equipment	95% (for 40 kg/ha)
		Soil solarization (SH)	SH can be employed in natural conservation ecosystems as an effective method	It should be used only in crop free soils and suitable climatic zones	90%(in tropical Indian condition), 86-99%(in California),

			of weed management as a non-chemical and non-destructive method.	and for low income crops	100%(in the UAE and rain fed rice field in India),
		Steam-Mobile soil steaming	Steaming leads to effective and long-term weed control by causing high mortality of weed seeds	It has severe effects on essential soil organisms in addition to weed seeds, and the soil takes a long time to recover from these effects. And this method uses fossil fuel.	90% (for 570 l/ha of diesel fuel per year)

Herbicides

Weeds can also be controlled using herbicides. Herbicides kill specific weeds with relatively little damage to crops. Some of these interfere with weed growth.

Identification of some common Herbicides [39]**:**

Vichete(Butachlor)

- Butachlor 50gm/kg
- Systemic herbicide for rice field
- Marketed by – Semco (Setu Pesticides Ltd.).
- Weed control in Aus, Aman and Boro
- Effective against different herbaceous annual, annual shrub, perennial and broad leaf weed
- This herbicide translocated through stem and root of weed after germination and kill them.
- Target weed: Boro shama, Holde Mutha, Boro chucha, Joyna, Pani katchu, Pani Long, Chechra, Sushni Shak, Zhill Marich, Dubra etc.
- Rate: 25 kg/ha – soil applied. 100 g covers one decimal land.
- Use: 2-3 days after transplanting of rice and maintain 1-2 inches water up to 7 days.

Butabel

- Butachlor 50 g/kg.
- Systemic herbicides for rice (pre-emergence)
- Marketed by – Corbel International Ltd.
- Weed control in Aus, Aman and Boro.

- Target weed: Boro shama, Holde Mutha, Boro chucha, Joyna, Pani katchu, Pani Long, Chechra, Sushni Shak, Zhill Marich, Dubra etc.
- Translocated through stem and root to the whole plant and kill them with root.
- Rate: 10 kg/acre. 1 kg covers 10 decimal of land.
- Use: Apply in the soil at 3-5 days after transplanting and maintain 1.5 to 2 inches water up to 2-3 days.

Mchlor

- Butachlor 50 g/kg.
- Systemic herbicide.
- Marketed by – ACI Ltd.
- Translocated through stem and root to the whole plant and kill them with root.
- Weed control in Aus, Aman and Boro.
- Target weed: Boro shama, Holde Mutha, Boro chucha, Joyna, Pani katchu, Pani Long, Chechra, Sushni Shak, Zhill Marich, Dubra etc.
- Rate: 25 kg/hectare. 1 kg cover 10 decimal land.
- Use: Apply in the soil at 3-5 days after transplanting and maintain 1.5 to 2 inches water up to 2-3 days.

Clear® 500 EC

- Pretilachlor 500 g/litre.
- Systemic herbicide in rice field.
- Selective herbicide.
- Target Weed: Boro shama, Choto shama, Panikachu, Chandmala, Zheel morich, Panilong, Malancha etc.
- Rate: 400 ml/acre. 20 ml/10 litre water for 5 decimal land.
- Use: 3-5 days after transplanting of rice seedling in 1-2 inches standing water.

Rifit® 500 EC

- Pretilachlor 500 g/litre.
- Systemic herbicide.
- Marketed by – Syngenta.
- Systemic and selective herbicide for weed control in rice field.
- Target Weed: Boro shama, Choto shama, Panikachu, Chandmala, Zheel morich, Panilong, Malancha etc.
- Rate: 400 ml/acre. 20 ml/10 litre water for 5 decimal of land.
- Use: 3-7 days after transplanting and 1-2 inches standing water.

Oxstar® 25 EC

- Oxadiazone 250 ml/litre.
- Selective and systemic herbicide in liquid form.
- Marketed by – Semco (Setu Pesticide).
- Target weed: Grasses and broadleaf weeds.
- Rate: 800 ml/acre. 40 ml Oxstar/10 litre water in tank for 5 decimal of land.
- Use: 6-8 days after transplanting. 1-2 inches standing water during spray.

Topstar® 400 SC

- 400 g/l Oxadiargyl.

- Marketed by – Bayer CropScience.
- Pre-emergence contact herbicide acting at the emergence of seedlings.
- Weed controls in rice, vegetables and onion
- Target weeds: Annual weeds (grasses and dicotelydon).
- Rate: 0.5 liter/ha for rice, 0.8-1.0 litre/ha for onion.
- Use: For rice, treat 3 days after transplanting, then water for 2 to 3 days after transplanting

Topstar® 80 WP

- 800 g/kg Oxadiargyl.
- Marketed by – Bayer CropScience.
- Pre-emergence, contact and selective herbicide acting at the emergence of seedlings.
- Weed controls in rice and onion
- Target weeds: Shama, holde mutha, boro chucha, pani kachu, tripotri shak, amrul shak.
- Rate: 75 g/ha for rice, 125 g/ha for onion.
- Use: For rice, treat 3 days after transplanting, then water for 2 to 3 days after transplanting

2,4-D® Amine

- 720 g 2,4-D/litre.
- Marketed by – Bayer CropScience.
- Broadleaf selective herbicide.
- Weed controls in tea and rubber.
- Target weeds: Mikania lata, pig weeds and other dicotyledonous weeds.
- Rate: 2.24 liter/ha, 45 ml/10 liter water for 5 decimal land.
- Use: spray in the ground.

Table- 14: Effect of herbicides on weeds in direct-seeded rice (mean of two years) [40]

	Weed count at 60 DAS (no./m2)				**Weed dry matter (g/m2)**		
Treatment	**Echinochloa spp.**	**Cyperus sp.**	**Digitaria sanguinalis**	**Dactylocteinum aegyptium**	**60 DAS**	**At harves**	**Weed control efficiency at harvest (%)**
Pendimethalin 0.75	3.4(13)	2.7 (6)	1.0 (0)	1.0 (0)	8.1 (66)	27.3 (759)	30.4
Pendimethalin 0.75 fb bispyribac 0.025	1.0(0)	1.0 (0)	1.0 (0)	1.0 (0)	1.0 (0)	1.0 (0)	100.0

Butachlor 1.50	4.0(19)	2.6 (6)	1.9 (3)	1.8 (2)	10.1 (101)	28.5 (823)	24.2
Butachlor 1.50 fb bispyribac 0.025	1.0(0)	1.0 (0)	1.9 (3)	1.7 (2)	4.2 (18)	11.1 (123)	88.6
Thiobencarb 1.50	4.0(19)	2.6 (6)	1.9 (3)	1.7 (2)	10.0 (101)	29.3 (865)	20.4
Thiobencarb 1.50 fb bispyribac 0.025	1.0(0)	2.8 (7)	2.0 (3)	1.7 (2)	4.3 (18)	11.2 (126)	88.3
Anilofos 0.375	4.1(19)	2.8 (7)	1.9 (3)	1.7 (2)	9.8 (96)	29.2 (876)	19.5
Anilofos 0.375 fb bispyribac 0.025	1.0(0)	1.0 (0)	1.9 (3)	1.8 (2)	4.4 (20)	10.9 (121)	88.7
Pretilachlor 0.75	4.2(20)	2.5 (5)	1.9 (3)	1.8 (2)	10.4 (107)	29.0 (851)	21.9
Pretilachlor 0.75 fb bispyribac 0.025	1.0(0)	1.0 (0)	1.9 (3)	1.7 (2)	4.4 (19)	11.4 (129)	88.0
Oxadiargyl 0.09	4.0(18)	2.6 (6)	1.9 (3)	1.7 (2)	10.4 (107)	29.1 (855)	21.4
Oxadiargyl 0.09 fb bispyribac 0.025	1.0 (0	1.0 (0)	1.8 (3)	1.7 (2)	4.4 (19)	10.8 (120)	88.8
Pyrazosulfuron-ethyl 0.015	4.3 (21)	2.7 (7)	2.0 (3)	1.8 (2)	10.4 (108)	29.5 (882)	19.0
Pyrazosulfuron-ethyl 0.015 fb bispyribac 0.025	1.0 (0)	1.0 (0)	2.0 (3)	2.0 (3)	4.3 (18)	11.2 (126)	88.3
Two hand weeding	1.0 (0)	1.0 (0)	1.0 (0)	1.0 (0)	1.0 (0)	10.6 (112)	89.4
Unweeded	6.1 (39)	2.8 (7)	2.1 (4)	1.9 (3)	17.2 (294)	32.7 (1077)	
LSD (P=0.05)	0.3	0.3	0.3	0.4	0.9	2.2	

Herbicides threaten the environment by polluting air, water and soil. It pollutes the soil and rainwater can carry these chemicals into a water reservoir which eventually pollutes the water reservoir and kills fish and other aquatic life.

1.3 Motivation

Weed management in rice field requires a lot of labor which increases the cost of production as weed management is implemented in traditional way by manual labor. Manual weeding requires 98 man-hours per hectare. There is a great opportunity to save labor input and cost up to 78% for weed control using mechanical methods [Ref*]. So we will try to use some efficient techniques of Machine Learning (ML) to detect weeds mechanically. For this we have chosen the Convolutional Neural Network (CNN), VGG16, InceptionV3 and DenseNet methods.

1.4 Objectives

Our main objectives are:

- Designing a system to detect the major weeds of rice field using machine learning methods.
- Based on that system, developing a mobile application which will detect the weeds in real time

1.5 Contribution

Our contributions are as follows:

- We prepared a unique dataset of 11 major weeds of rice field of Bangladesh.
- We built a machine learning based system including 4 prominent machine learning algorithms which can detect the rice field weeds with a high accuracy.
- We developed a mobile app to detect the rice field weeds in real time based on our built system

1.6 Related Work

There is some information technology based efficient weed detection methods using Machine Learning and Internet of Things (IoT).

In [41], the authors introduced the advances of weed detection using ground-based machine vision with appropriate image processing methods that can detect 98.7% of weeds. Specifically, four methods, namely, pre-processing, segmentation, feature extraction and classification for weed detection were presented in detail. Different color indices and classification methods were developed to distinguish vegetation from the background, color index-based, edge-based and learning-based. One of the difficulties in weed identification was in discriminating between crops and weeds, which often had similar characteristics. Generally, four categories of features, namely, biological morphology, spectral features, visual texture and spatial context, were used for this work, which were discussed in this paper. They also presented the application of conventional machine learning-based and recently developed deep learning-based methods for weed detection.

Though ground-based machine vision and image processing techniques were an effective method but it required large number of labeled sample as training data and it also required a lot of labor.

In [42], the authors proposed a cabbage identification and pesticide spraying control system based on an artificial light source. Classification and Identification of Support Vector Machines (SVM) with the image skeleton point-to-line ratio and ring structure features, a contrast test of different feature combinations of a support vector machine was performed and the optimal feature combination of the SVM and its parameters were determined. Also, a targeted pesticide spraying control system were designed based on an active light source and a targeted spraying delay model, besides, a communication protocol for the targeted spraying control system based on electronic control unit was developed to realize the controlled pesticide spraying of targets. According to the support vector machine classification test results, the feature vector composed of point-to-line ratio according to a real field application test results, the average detection accuracy of cabbage was 95.0%, the average detection accuracy of weeds was 93.5%. And the results of target spraying at three operating speeds of 0.52m/s, 0.69m/s and 0.93m/s showed that the average invalid spraying rate, average miss spraying rate and average effective spraying rate were 2.4, 4.7 and 92.9%, respectively. respectively. Furthermore, it was also found from the results that with increasing speed, the offset of the center of mass of the target increased and reached a maximum value of 28.6 mm when the speed was 0.93m/s.

In [43], the authors explored the potential of machine learning algorithms for weed and crop classification from UAV images. Weed detection in crops was a challenging task which was solved by ortho- mosaicking of the image, feature extraction and labeling of images for training machine learning algorithms. Basically in this paper, the performance of several machine learning algorithms, Random Forest (RF), Support Vector Machine (SVM) and k-nearest neighbors (KNN) was analyzed to detect weeds using UAV images collected from a pepper crop field located in Australia. The evaluation metrics used in performance comparison were accuracy, precision, recall, false positive rate and kappa coefficient. MATLAB was used to simulate machine learning algorithms; And the achieved weed detection accuracy was 96% using RF, 94% using SVM and 63% using KNN.

The paper [44] proposed a real-time weed detection system that uses machine learning to identify crop weeds and stereo vision for 3D crop reconstruction. To create a 3D point cloud of a firm, structures from motion techniques were applied on the videos taken. Convolutional Neural Network (CNN) and ResNet-50 algorithm were used on two manually generated datasets of cucumber and onion crops for training machine learning models. It was seen that the ResNet-50 model performs better than the convolution neural network model in detecting weeds. The ResNet-50 model performed an overall accuracy of 84.6% for the cucumber dataset while it showed 90% accuracy for the onion crop dataset.

The paper [45] proposed using machine learning and satellite imagery to monitor and manage the spread of gamba grass (*Andropogon gayanus*) as it was spreading through the tropical savannas of northern Australia, which could have devastating ecosystem consequences, including increased fire intensity. They prepared field data supervised learning of very high-resolution (0.3 m) WorldView-3 satellite imagery and tuned the hyperparameters of an extreme gradient boosting classifier to produce a viable solution for detecting the probability of gamba grass presence. To evaluate the performance of WorldView-3 imagery in discriminating gamba grass, they tested the usefulness of the predictors derived from: 1) spectral bands; 2) textural features; 3) spectral indices; and 4) all predictors combined. The results showed that under optimal environmental conditions their system can map the presence of gamba grass from space with up to 91% accuracy.

In [46], using neural networks (NN), 99% accuracy was achieved to detect the weeds in rice field. The images of weeds were taken from 50 meter above of the field with a 16.1 megapixels CMOS camera which was mounted on a drone. To train the NN, Gray-Level Co-Occurrence Matrix (GCLM) with Haralicks descriptor were used for texture classification as well as Normalized Difference Index (NDI) for color. The captured images were of low resolution as they were taken at 50-meter-high over the ground.

In [47], the authors proposed an architecture for Internet of Things (IoT)-based smartweed detection that minimizes human intervention in the field and instead improves training models by considering subjective information stored on servers. To achieve this task, real-time robots were used that can accurately identify vegetation and thereby classify it into crops and weeds using a trained classification model. The Internet of Things (IoT) retrieved and stored predictive data that can be accessed in real-time by weed-detecting robots.

The paper [48] focused on detecting the weeds in the crop using convolutional neural network (CNN), Image processing and IOT. The CNN model was first trained with large images of weeds and crops and then the trained CNN model was deployed on the Raspberry Pi. The Raspberry-Pi based machine learning system collected the images supplied from the camera and then performed image segmentation by dividing the image into smaller segments using a segmentation algorithm – Watershed Segmentation Algorithm. Each segment was passed to a trained CNN model to classify it as weeds or crops. If it was weed, the area was marked as weed in the original image. In this method all the weed parts were identified and the identified image can be sent to the farmers via email. This system was trained using 250 images of weeds and crops and gave an average accuracy of 85%, an average false positive ratio of 7%, an average false acceptance ratio of 2.6%.

Table- 15: Related work

Author	**Problem Definition**	**Used Technology**	**Findings from paper**	**Limitations**	**Accuracy**
Aichen Wang [41]	Weed detection using Machine Learning	Machine Vision	Machine vision with appropriate image processing algorithms is a promising tool for precise real-time weed detection in the field.	It requires a large number of labeled sample for training. And it lacked generality and robustness. This process is laborious also.	98.7%

Zhao Xueguan [42]	Weed detection using Machine Learning	Support Vector Machine (SVM)	Designed to prevent changes in natural lighting on the target by using an active light source. Three operation speeds were tested, invalid spraying rate 2.4%, average missed spraying 4.7%, and average effective spraying rate 92.9%	Sometimes weeds are mistakenly identified, because of their local reflections and own growth characteristics or they partially overlap with crops.	93.5%
Nahina Islam [43]	Weed detection using Machine Learning	Random Forest (RF), Support Vector Machine (SVM) and k-nearest neighbors (KNN)	RF and SVM algorithms are more efficient and practical to use detect weeds from UAV images than KNN	Data collection from UAVs into meaningful information is a difficult task. it requires significant of manual effort for segment size tuning, feature selection design.	96% using RF, 94% using SVM and 63% using KNN
Siddhesh Badhan [44]	Weed detection using Machine Learning	CNN and RestNet-50	CNN and RestNet-50 are trained on 3 datasets. Detecting weeds improved in real-time. The system can be used in existing weed detection robots.	Low-resolution video can reduce accuracy. Training time is long due to real time on the input video of the crops fields.	84.6% using RestNet-50 and 90% using CNN
Yuri Shendryk [45]	Weed detection using Machine Learning	Machine Learning and Satellite Imagery	This approach would work well for large-scale monitoring of gamba grass over large areas as it relies exclusively on readily	High education are required for this technology.	91%

			available VHR satellite imagery.		
Oscar Barrero [46]	Weed detection using Machine Learning	Neural Networks (NN)	Images were taken from a drone and high level of precision seen in this trained NN.	The process takes long time for big image file. The captured images were of low resolution as they were taken at 50 meter high over the ground.	99%
Fenil Dankhara [47]	Weed detection using Internet of Things(IoT)	Internet of Things (IoT)	A remote modeled robot is equipped with the Raspbian operating system, Weed classifier Raspberry pi, Pi Camera v2, Sprayer.	-	-
Shweta Kulkarni [48]	Weed detection using IoT based image processing and CNN	IoT, Image processing and CNN	The system is trained with 250 images of crop and weed with a camera attached to Raspberry pi based Machine Learning module. Then the images are classified by CNN.	-	85%

Chapter 2

Proposed Methodology

2.1 Convolutional Neural Network (CNN)

2.1.1 Introduction

Convolutional Neural Network or **CNN** is a widely used tool in computer vision technology to analyze visual images. It is analogous to human optical system. Human eyes are quick responsive to external circumstance and quickly passes the inspected image to brain through trillions of neurons and finally classified in the brain taking help of knowledge gathered from previous experience. This exact strategy is followed in **CNN**. A **CNN** model is first trained with sufficient number of training samples then new samples are given as input and after processing throughout the **CNN** architecture classified based upon the comparison with trained samples.

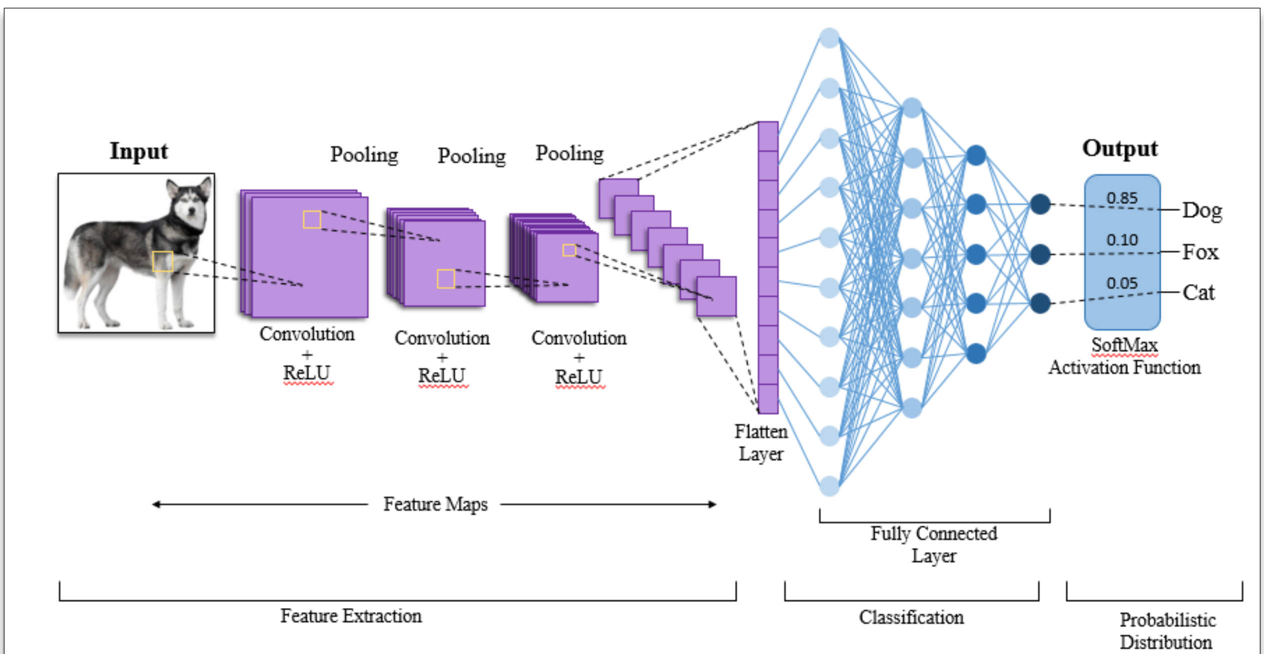

Figure- 05: Convolutional Neural Network (CNN) Architecture

As computers work with numerical data so we need to convert Image to computer readable format. RGB color scheme can represent an image in matrix form which is easily understandable by computers. This RGB matrices are feed through different layers of CNN described below:

2.1.2 Architecture

Convolution Layer: An input matrix is convolud with a filter of smaller size that identifies the significant features of the input and produces feature map. The Kernel (feature) slides throughout the whole input matrix in a certain amount (which is called stride). Resultant matrix cells are filled by summing up the products of Kernel and filter mathematically can be expressed as:

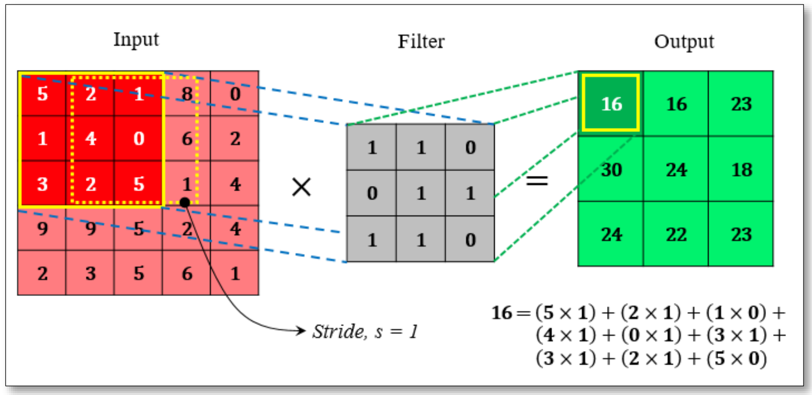

Figure- 06: Convolution operation

$$\boldsymbol{Result_{i,j}} = \sum_{i=1}^{3}\sum_{j=1}^{3}(\boldsymbol{input_{i,j}} * \boldsymbol{filter_{i,j}})$$

Same Padding is used to preserve the actual size of the image. It just adds an extra row of empty bits (0) in all surrounding sides that reduces the risk of image quality degradation. Different types of filters are available to serve user specific needs like blur, sharpen edge, detect edge etc. [49].

Activation Functions: Recalling to our brain analogy, a neuron is fired when reaches a certain energy potential propagated from the previous neuron. Activation function serves the similar purpose for propagation of features throughout the different layers of CNN. If the output value of activation function crosses a certain threshold, it then passes the features to the next neurons. Moreover, they add Non-linearity to the data that can represent much real world data that have higher degrees of complexities.

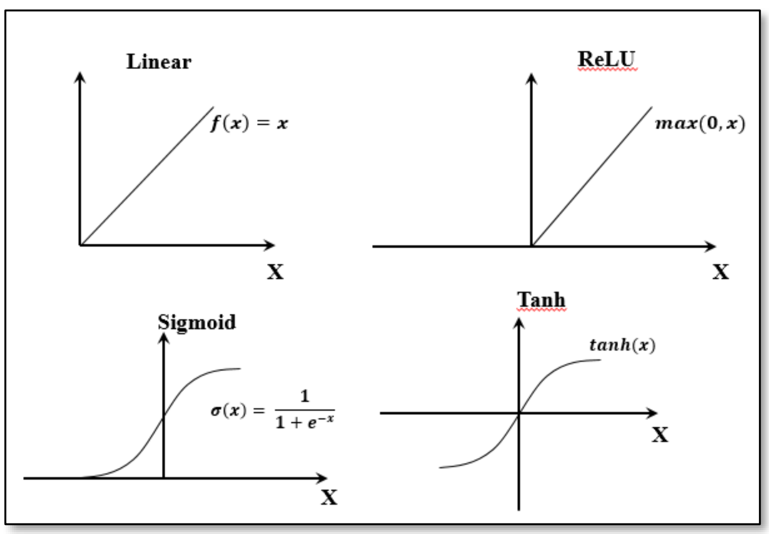

Figure- 07: Various Activation functions

There are different activation functions as described below [50]:

Linear: $f(x) = x$

It gives same output as input thus provides a straight linear equation which is not good enough to model higher order data hence used infrequently.

Sigmoid: $\sigma(x) = \frac{1}{1+e^{-x}}$

It gives output ranging 0 to 1 which is suitable for modeling probabilities. Adds non linearity in output.

tanh: $tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$

This is an extension of sigmoid function which gives output ranging -1 to +1. It also adds non linearity in output.

ReLU: $f(x) = \max(0, x)$

Discards the negative values from feature maps. Provides feature map consisting only non-negative values

Softmax: $\sigma(\vec{z}) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$

It provides probability distributions from the input vectors that help to predict the right most one from multiclass samples. Value ranges from 0 to 1.

A question arises on which function is best. There is no hard and fast answer to this, but conventionally ReLU is used for hidden layers for simplicity and better results. On the output side softmax activation function is used for Multiclass classification problems and Linear activation function is used for regression problems [51].

Pooling Layer: Feature maps are passed through pooling layers for down sampling preserving significant features. Any type of pooling may happen depending on user requirement. Max pooling picks the most intense pixel from the feature map. Average pooling makes average and assigns it for all cells. Sum pooling sums up all the pixels of the feature map. A stride is maintained while sliding over the feature map.

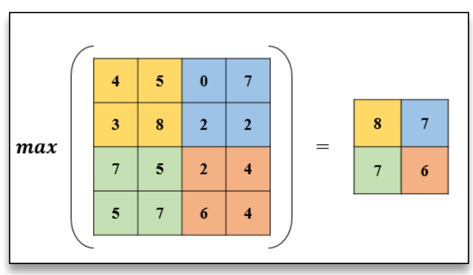

Figure- 08: Max Pooling

After processing at pooling layer now we have much compact feature matrixes which are in two dimensional forms. A flattening layers converts these matrices in Vectors and Pass through Fully connected layers consist of neurons. At the end of connected layers Output layer gives us the probability distributions for the input vectors.

2.1.3 Gradient Descent

Gradient descent is an optimization algorithm commonly used for training machine learning models and neural networks. Training data helps these models learn over time, and the cost-function in gradient descent specifically acts as a barometer, measuring its accuracy with each iteration of parameter updates. The model will continue to adjust its parameters to obtain the smallest possible error until the function is close to or equal to zero [52].

A gradient for an n dimensional function $f(x)$ at a given point p as defined as follows [53]:

$$\Delta f(p) = \begin{bmatrix} \frac{\partial f}{\partial x_1}(p) \\ \vdots \\ \frac{\partial f}{\partial x_n}(p) \end{bmatrix}$$

Working Procedure of Gradient Descent [53]

The gradient descent algorithm iteratively calculates the next point using the gradient of the current position, scales it by the learning rate, and subtracts the value obtained from the current position to create a step.

The process can be written as:

$$p_{n+1} = p_n - \eta \nabla f(p_n)$$

Here, η is an important parameter that scales the gradient and controls the step size. In machine learning, this is called learning rate which has a strong impact on its performance.

- The smaller learning rate the longer GD converges, or may reach maximum iteration before reaching the optimum point.
- If the learning rate is too big the algorithm may not converge to the optimal point (jump around) or even to diverge completely.

Simply the algorithm is:

1. Choose a starting point (initialization)
2. Calculate gradient at this point
3. Make a scaled step in the opposite direction to the gradient (objective: minimize)
4. Repeat points 2 and 3 until one of the criteria is met:
    4.1 Maximum number of iterations reached
    4.2 Step size is smaller than the tolerance (due to scaling or a small gradient)

Learning rate [54]

Learning rate is referred to as the step size considered to reach the minimum or the lowest point. Typically, the learning rate is a small value that is evaluated and updated based on the behavior of the value function. If the learning rate is high, the step becomes larger but the risk of overshoot is reduced. At the same time, the lower learning rate reduces the step size, which affects the overall efficiency but facilitates more accuracy of the system.

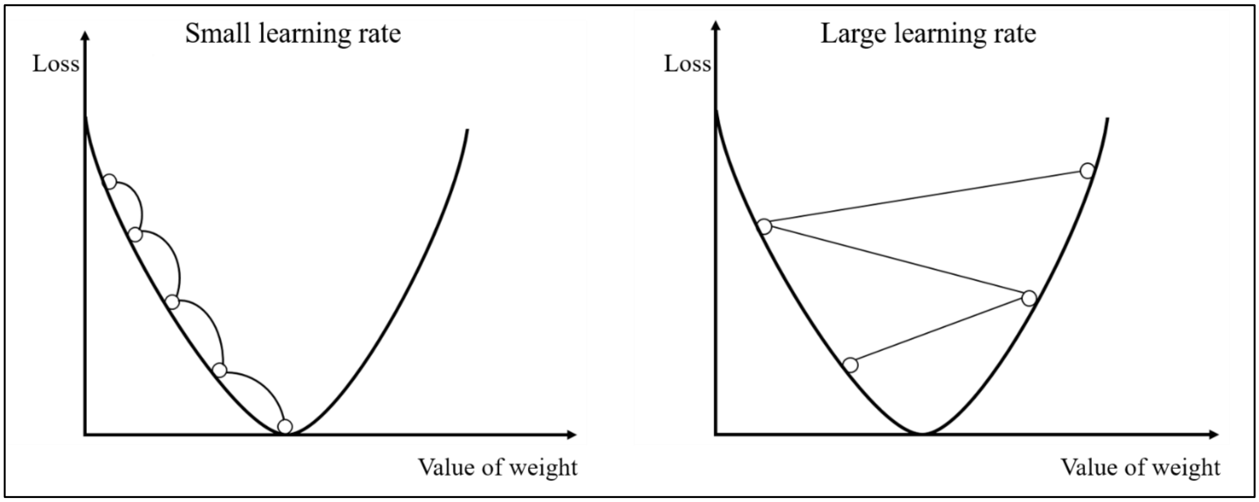

Figure- 09: Learning rate of Gradient Descent

Cost function

Cost function is defined as a measure of the difference or error between the actual value and the expected value at the current location and appears as a single real number. It helps to increase and improve machine learning skills by providing feedback to this model so that it can reduce errors and find local minimum or global minimum. Further, it repeats continuously along the direction of negative gradient until cost function approaches zero. At this steep descent point, the model stops learning. Although cost function and loss function are considered synonymous, there is a small difference between them- This is about the error between training machine learning models, where the loss function refers to the error of a training instance and a cost function calculates the average error across an entire training set.

Based on the error of different training models, the gradient descent learning algorithm can be divided into batch gradient descent, stochastic gradient descent and mini-batch gradient descent. Among them the stochastic gradient descent is easier to allocate in desired memory and relatively fast to compute and most importantly, is more efficient for large datasets than the other two methods [54].

2.1.4 Stochastic Gradient Descent [55]

The word 'stochastic' means a system or process which is linked with a random probability. In Stochastic Gradient Descent (**SGD**), for each iteration a few samples are randomly selected instead of the entire data set. Since only one training sample is required at a time, it is relatively easy to store in allocated memory.

The algorithm is as follows [55]**:**

```
for i in range (m):
        θ_j = θ_j − α(ŷ^i − y^i)x_j^i
```

$$\boldsymbol{\theta_j = \theta_j - \alpha(\hat{y}^i - y^i)x_j^i}$$

In SGD, as for each iteration randomly only one sample from the dataset is chosen, the algorithm reaches the minima usually noisier than typical gradient descent algorithm. But this is not so important because the path taken by the algorithm does not matter, because the algorithm reaches the minima in a significantly shorter training time.

A path chosen by SGD [55]**:**

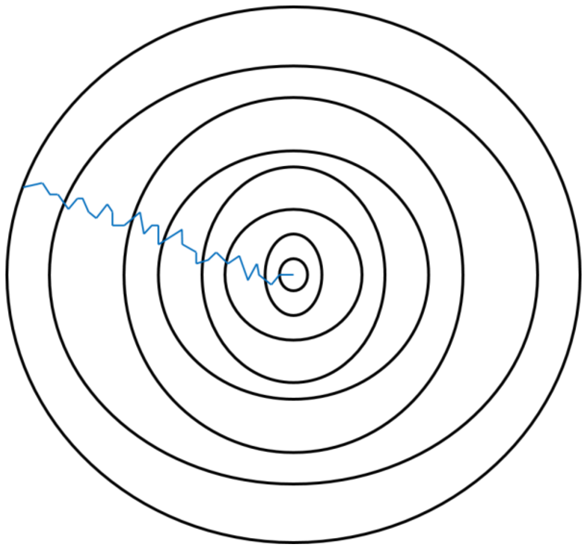

Figure- 10: Path chosen by SGD

Importantly, since SGD is usually noisier than typical gradient descent algorithm, due to its randomness it usually takes a much larger number of iterations to reach the minima and it is computationally much less expensive than typical gradient descent.

Pseudocode for SGD in Python [55]**:**

```
def SGD(f, theta0, alpha, num_iters):

    theta = theta0
    for iter in range(num_iters):
        grad = f(theta)[1]

        theta = theta - (alpha * grad)

    return theta
```

2.2 VGG16 [56] [57]

2.2.1 Introduction

VGG16 is a type of Convolutional Neural Network (CNN) model that is considered one of the best computer vision models. It is an object detection and classification algorithm capable of classifying 1000 images of 1000 different categories with 92.7% accuracy and is easy to use with transfer learning. The authors of this model have increased the depth by using an architecture with a very small (3 × 3) convolution filter to evaluate the networks thoroughly, which shows a significant improvement over previous prior-art configurations. They pushed the depth to 16-19 weight levels making it around 138 trainable parameters. The '16' in VGG16 refers to 16 layers with weights.

2.2.2 Architecture

VGG16 consists of 13 convolutional layers, 5 max pooling layers and 3 density layers. That is, it has a total of 21 layers with only sixteen weight layers. Its input tensor size is 224, 244 with 3 RGB channels. What makes VGG16 unique is that it works with the convolution layer of the 3x3 filter with stride 1 and always uses the same padding and maximum pool level of the 2x2 filter of stride 2 instead of having a large number of hyper-parameters where the convolution and max pool layers are arranged consistently across the architecture. Conv-1 layer has 64 filters, Conv-2 has 128 filters, Conv-3 has 256 filters, Conv-4 and Conv-5 have 512 filters. Three fully-connected layers follow a stack of convolutional layers where the first two has 4096 channels, the third performs a 1000-way ImageNet Large Scale Visual Recognition Challenge (ILSVRC) classification and thus has 1000 channels for each class. The final layer is the soft-max layer.

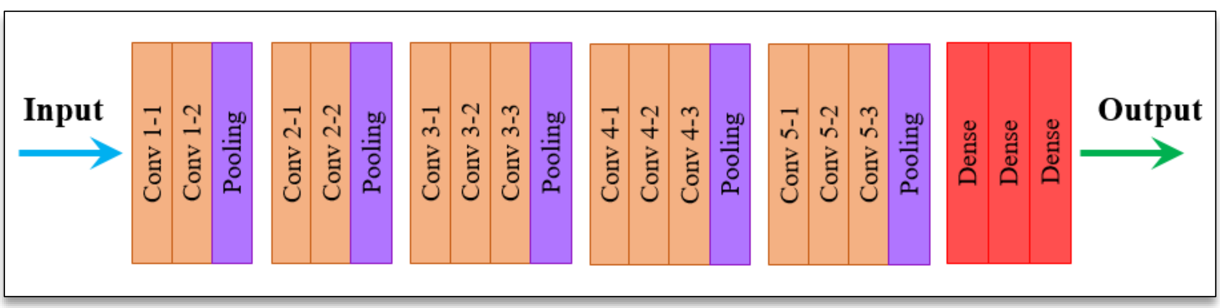

Figure- 11: Architecture of VGG16

2.3 InceptionV3 [58]

2.3.1 Introduction

InceptionV3 is a multi-scale architecture that uses filters of various sizes to process input images at multiple scales and capture information at different levels of abstraction. The network consists of a series of convolutional and pooling layers, followed by fully connected layers, and ends with a softmax classifier that outputs class probabilities.

InceptionV3 is a modification of the previous Inception architecture and is designed to address some of the limitations of the earlier version. It is characterized by the use of Inception modules, which are building blocks that extract features from input data at multiple scales and then concatenate the results. This allows the network to learn features from a variety of scales, which can improve its ability to recognize objects in images and make it more robust to changes in object size or viewpoint.

InceptionV3 has been widely used in various computer vision tasks such as image classification, object detection, and semantic segmentation, and has achieved state-of-the-art performance on several benchmark datasets.

2.3.2 Architecture

The architecture of InceptionV3 consists of a series of convolutional and pooling layers, followed by multiple fully connected layers, and ends with a softmax classifier that outputs class probabilities. InceptionV3 is a deep convolutional neural network (DCNN) architecture that consists of multiple layers of convolutional, pooling, and fully connected layers. At the core of the architecture are the Inception modules, which are building blocks of the network. Each Inception module consists of multiple parallel branches, each of which performs a different operation on the input. The output of each branch is concatenated and fed as input to the next layer. This allows the network to extract information from the input image at multiple scales and capture complex features.

The first layers of the network consist of a series of convolutional and pooling layers that extract low-level features from the input image. This is followed by multiple Inception modules, which gradually increase the size of the convolutional filters and extract increasingly complex features.

The final layers of the network consist of a series of fully connected layers that produce a class prediction. The output of the final fully connected layer is fed through a softmax activation function, which outputs class probabilities.

The InceptionV3 architecture also includes several modifications aimed at improving performance, including the use of batch normalization and the use of an auxiliary classifier.

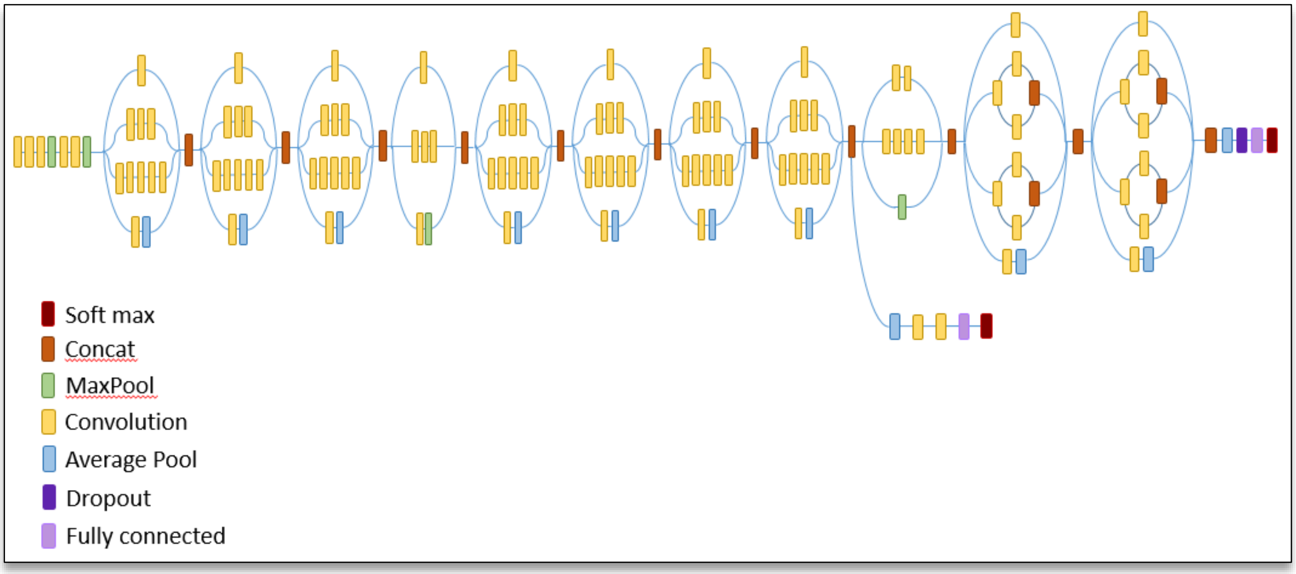

Figure- 12: Basic Architecture of InceptionV3

2.4 DenseNet [59]

2.4.1 Introduction

The dense convolutional Network (DenseNet) connects each layer to every other layer. In CNN L layers have L direct connection- one between each layer. This network has $\frac{L(L+1)}{2}$ direct connection for L layers. All preceding layers are used as inputs and its own feature-maps are used as inputs into all subsequent layers, for each layers.

It connects all layers directly with each other, each layer obtains additional inputs from all preceding layer and passes on its own feature-maps to all subsequent layers. Its own feature-maps are passed on to all $L-\ell$ subsequent layers. It makes $\frac{L(L+1)}{2}$ connections in an L-layer network, instead of just L. There is no need to re-learn redundant feature-maps, it requires fewer parameters. The final classifier makes a decision based on all feature-maps in the network, DenseNet layes are very narrow adding only small set of feature-maps. Advantage of DenseNets is their improved flow of information and gradients throughout the network. Each layer has direct access to the gradients from the loss function and the original input signal. It makes data easy to train and leading to an implicit deep supervision.

2.4.2 Architecture

Dense connectivity:

It introduces direct connection from any layer to all subsequent layers. Consequently, the ℓ th layer receives the feature-maps of all preceding layers, $x0, \ldots, x\ell-1$, as input:

$$x\ell = H\ell([x0, x1, \ldots, x\ell-1])$$

where $[x0, x1, \ldots, x\ell-1]$ refers to the concatenation of the feature-maps produced in layers $0, \ldots, \ell-1$. For ease of implementation, we concatenate the multiple inputs of $H\ell(\cdot)$ in equation into a single tensor.

Composite function:

$H\ell(\cdot)$ as a composite function of three consecutive operations: batch normalization (BN), followed by a rectified linear unit (ReLU) and a 3×3 convolution (Conv).

Pooling layers:

The concatenation operation used in Equation is not viable when the size of feature-maps changes. However, an essential part of convolutional networks is down-sampling layers that change the size of feature-maps. To facilitate down-sampling in our architecture we divide the network into multiple densely connected dense blocks. Layers between blocks as transition layers, which do convolution and pooling. The transition layers used in our experiments consist of a batch normalization layer and a 1×1 convolutional layer followed by a 2×2 average pooling layer.

Growth rate:

If each function $H\ell$ produces k feature-maps, it follows that the ℓ th layer has $k0 + k \times (\ell-1)$ input feature-maps, where k0 is the number of channels in the input layer. Each layer has access to all the preceding feature-maps in its block and also to the network's. Feature-maps are the global state of the network. Each layer adds k feature-maps of its own to this state. How much new information each layer contributes to the global state, it regulated by the growth rate. After one time written, the global state can be accessed from everywhere within the network, where traditional network architectures, cannot be accessed from everywhere there is no need to replicate it from layer to layer. Small growth rate is sufficient to obtain state-of-the-art results.

Bottleneck layers:

Each layer only produces k output feature-maps. It usually has many more inputs. It has been observed in Inception networks and ResNets that a 1×1 convolution can be introduced as bottleneck layer before each 3×3 convolution. So that it reduces the number of input feature-maps and this improve computational efficiency. This design especially effective for DenseNet and the BN-ReLU-Conv (1× 1)-BN-ReLU-Conv(3×3) version of $H\ell$, as DenseNet-B. It can produce 1×1 convolution into 4k feature-maps.

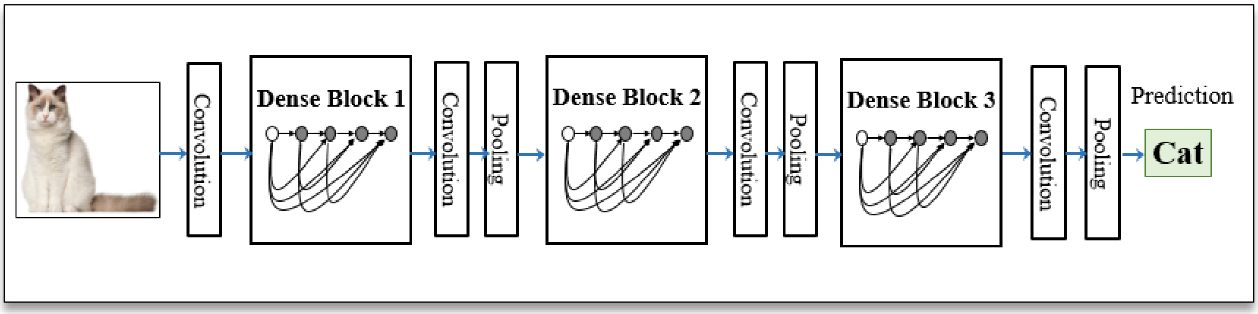

Figure- 13: Basic Architecture of DenseNet

Chapter 3

Proposed Model

We have trained the 4 models- CNN, VGG16, InceptionV3 and DenseNet which are described in methodology chapter to detect the weeds on a unique dataset of our own which contains more than 4,300 digital images of different 11 weeds. The algorithms will detect the images using image classification technique. To train the algorithms, we first preprocessed the data or images so that the models can be trained fast and accurately. Then we trained the models.

3.1 Data Preprocessing

As per number of weeds we created 11 folders and named them after the scientific name of the weeds. Images are categorized according to the name of the weeds using categorical variable (e.g., Commelina benghalensis folder contains pictures of Commelina benghalensis weed).

Since the size of each image is not same- every image has different size, we stated the image size: 150×150. Again every image's pixel range is from 0 to 255, this range is too large for numerical computation and the system is also unable to be trained well. So, we stored the image data into an array and the array was reshaped into 150×150×3 array of floats with each value divided by 255 so that all values are between 0 and 1. Then the images were divided into training data and testing data, 80% images were used as training data and 20% images were used as testing data.

3.2 Model Training

We designed the system in such a way that each model is trained in the same way. As we mentioned before, the models detected the weeds in image classification method. Firstly, the data were augmented so that the models are trained well. Then the augmented data sent to the model as input. We used Softmax activation function as the models would classify multiclass classification. ADAM optimizer was used as optimization algorithm and Categorical Cross Entropy function was used as loss function. ADAM optimization algorithm is used to update network weights based on training data. This algorithm works better than classical stochastic gradient descent algorithm. On the other hand, Categorical Cross Entropy is a type of loss function used in supervised learning problems with categorical labels. This loss function is used in classification tasks.

We set callback function to monitor and to avoid over fit. **acc_calback** was used so that the system stops learning when the training accuracy reaches 99.99%. **EarlyStopping** callback was used in such a way that the model stopped learning if the validation loss did not decrease until 15 epochs. The **ReduceLROnPlateau** callback was used such that the learning rate was reduced by a factor of 0.1 if the model ran for 5 epochs without losing validation. The '**Modelcheckpoint**' callback was used so that the model that achieved the lowest validation loss would be stored in a defined folder.

Then we ran K-fold cross validation on our training data, where the value of K-fold was set to 5. From the 80% of training data, 70% of data was used for training data and the rest 10% data was used for validation. So the models ran the training process 5 times, each time using a different subset as the validation dataset. The epoch and batch size was set to 100 and 128 respectively. So the model was trained 5 times and run for 100 epochs each time with a batch size of 128.

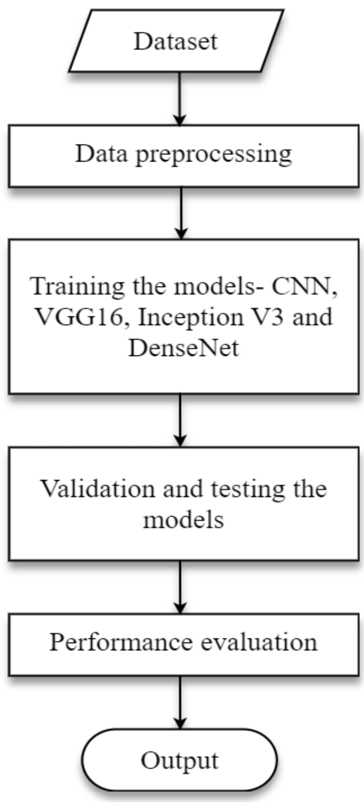

Figure- 14: Architecture of proposed model

3.3 Android App Development

Based on the system an android mobile app was developed using Android Studio to detect the weeds in real time

Chapter 4

Result Analysis

To evaluate the performance of our proposed model, a set of evaluation metrics consisting of Accuracy, Precision, Recall, F1-Score, Confusion Matrix and ROC - AUC were used in each model. The results obtained for each model are documented below:

4.1 Result Analysis of the Models

4.1.1 CNN

For the CNN model,

- The classification report of Precision, Recall, and F-1 Score against each class are stated below:

Table-16: Classification report for CNN

Sl. No	**Class**	**Precision**	**Recall**	**F-1 Score**
1	*Alternanthera philoxeroide*	90.91	71.43	80.00
2	*Centella asiatica*	93.65	71.95	81.38
3	*Commelina benghalensis*	77.89	93.67	85.05
4	*Cyperus ochraceus*	76.47	81.25	78.79
5	*Fimbristylis littoralis*	89.47	97.14	93.15
6	*Ipomoea aquatic*	98.26	96.57	97.41
7	*Marsilea minuta*	76.60	86.75	81.36
8	*Panicum repens*	86.11	89.86	87.94
9	*Paspalum scrobiculatum*	76.24	82.80	79.38
10	*Pteris vittata*	91.35	92.23	91.79
11	*Synedrella nodiflora*	91.35	92.23	91.79

- Obtained accuracy of CNN model is 87%

- Confusion matrix is stated below:

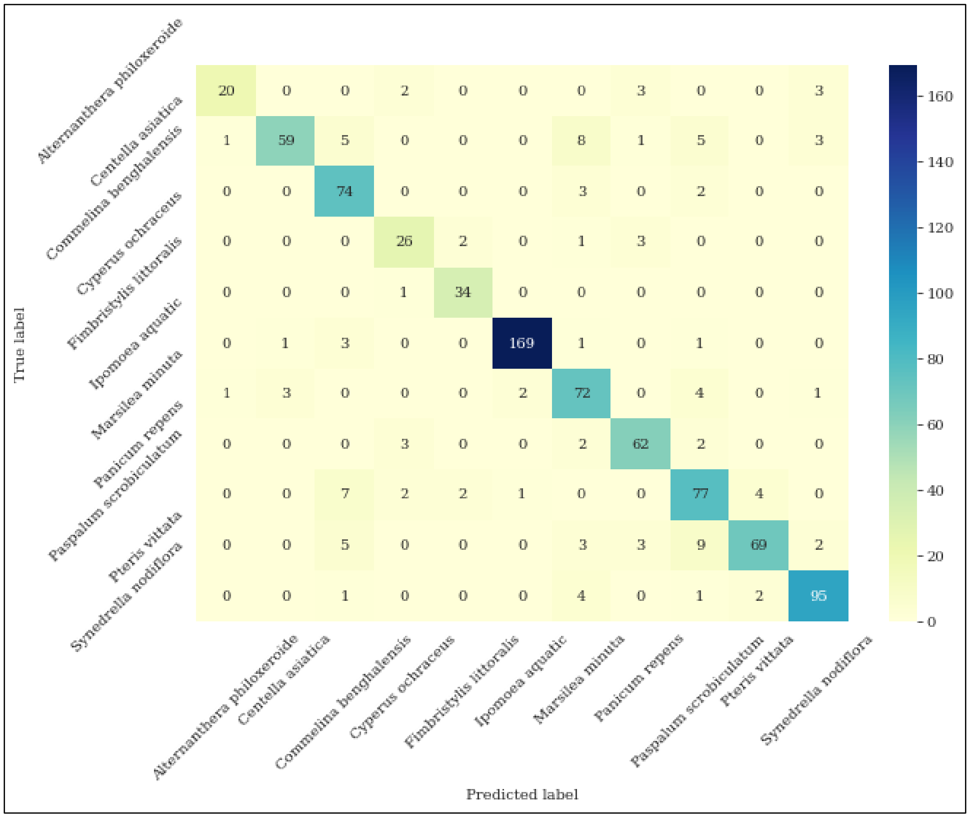

Figure-15: Confusion Matrix for CNN

- ROC AUC score is 0.9205 and the corresponding curve is:

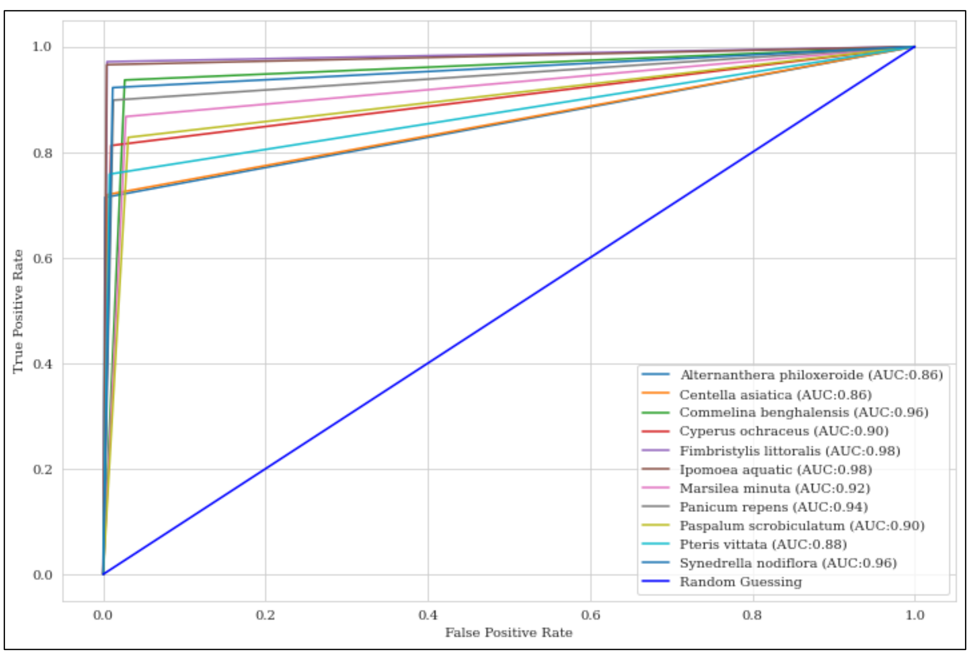

Figure-16: ROC AUC curve for CNN

4.1.2 VGG16

For the VGG16 model,

- The classification report of Precision, Recall, and F-1 Score against each class are stated below:

Table-17: Classification report for VGG16

Sl. No	Class	Precision	Recall	F-1 Score
1	*Alternanthera philoxeroide*	95.65	78.75	86.27
2	*Centella asiatica*	93.02	97.56	95.24
3	*Commelina benghalensis*	95.12	98.73	96.89
4	*Cyperus ochraceus*	84.21	100.00	91.43
5	*Fimbristylis littoralis*	83.33	85.71	84.51
6	*Ipomoea aquatic*	100.00	98.86	99.43
7	*Marsilea minuta*	98.73	93.98	96.30
8	*Panicum repens*	91.43	92.75	92.09
9	*Paspalum scrobiculatum*	95.79	97.85	96.81
10	*Pteris vittata*	98.90	98.90	98.90
11	*Synedrella nodiflora*	97.94	92.23	95.00

- Obtained accuracy of VGG16 model is 96%

- Confusion matrix for VGG16 is stated below:

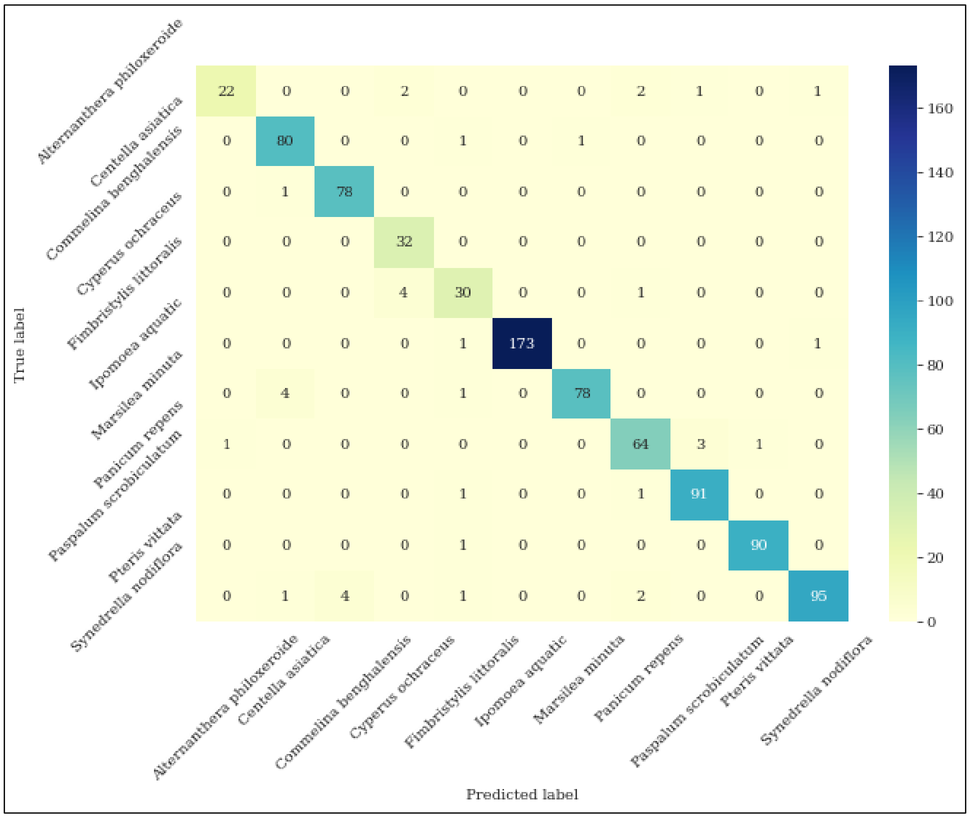

Figure-17: Confusion Matrix for VGG16

- ROC AUC score of VGG16 is 0.9684 and the corresponding curve is:

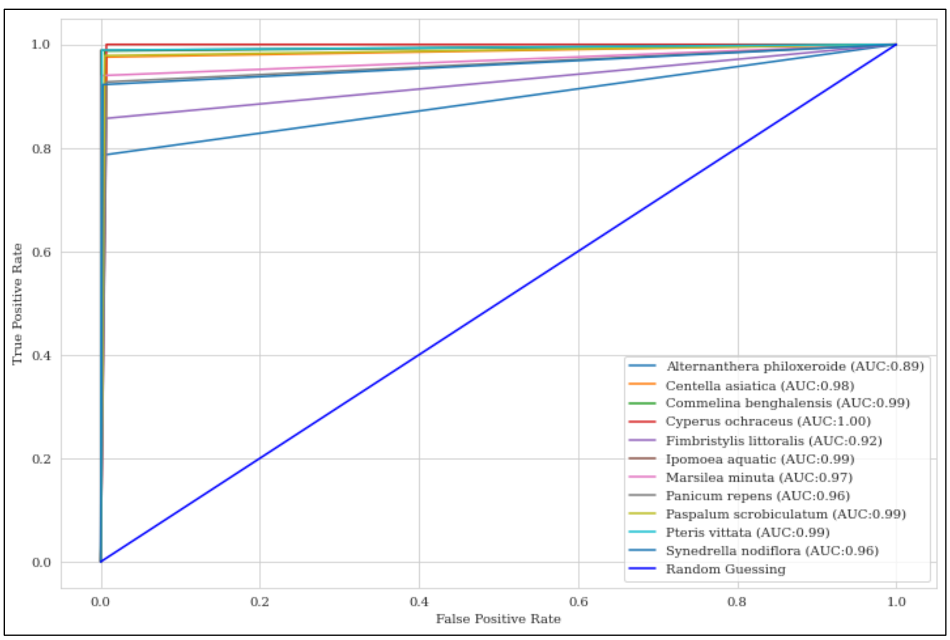

Figure-18: ROC AUC curve for VGG16

4.1.3 InceptionV3

For the InceptionV3 model,

- The classification report of Precision, Recall, and F-1 Score against each class are stated below:

Table-18: Classification report of InceptionV3

Sl. No	Class	Precision	Recall	F-1 Score
1	*Alternanthera philoxeroide*	95.45	75.00	84.00
2	*Centella asiatica*	93.98	95.12	94.55
3	*Commelina benghalensis*	96.25	97.47	96.86
4	*Cyperus ochraceus*	87.88	90.62	89.23
5	*Fimbristylis littoralis*	97.06	94.29	95.65
6	*Ipomoea aquatic*	96.61	97.71	97.16
7	*Marsilea minuta*	90.00	86.75	88.34
8	*Panicum repens*	79.01	92.75	85.33
9	*Paspalum scrobiculatum*	94.74	96.77	95.74
10	*Pteris vittata*	100.00	93.41	96.59
11	*Synedrella nodiflora*	88.00	85.44	86.70

- Obtained accuracy of InceptionV3 model is 93%

- Confusion matrix for InceptionV3 is stated below:

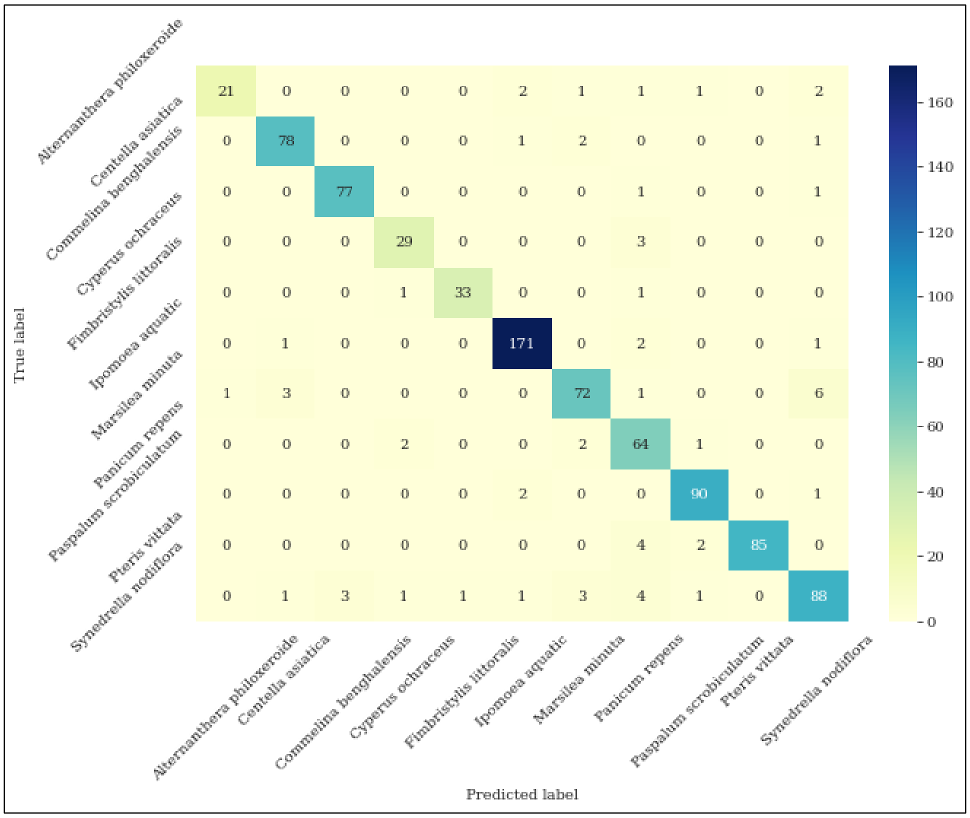

Figure-19: Confusion Matrix for InceptionV3

- ROC AUC score of InceptionV3 is 0.9533 and the corresponding curve is:

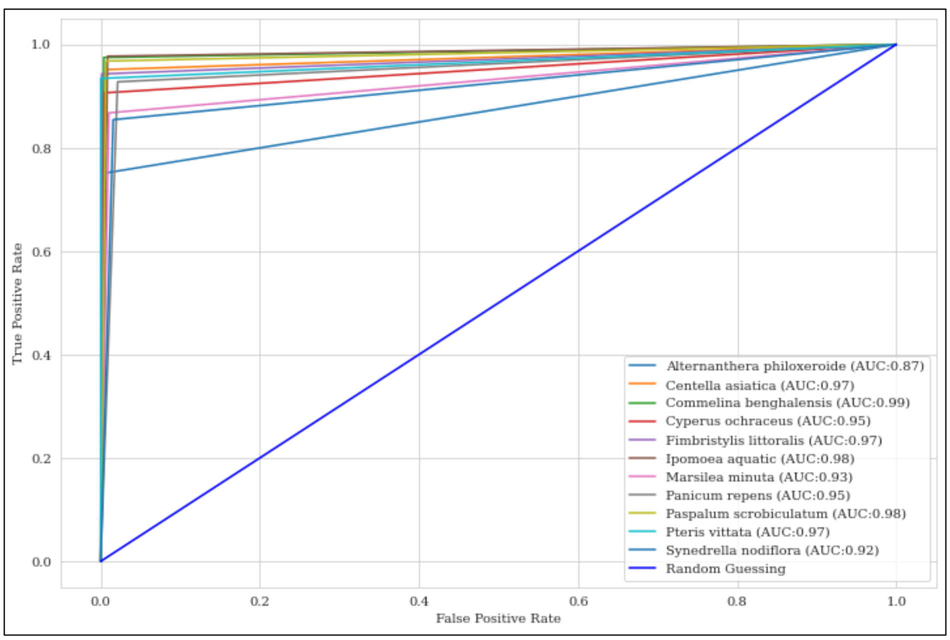

Figure-20: ROC AUC curve for InceptionV3

4.1.4 DenseNet

For the DenseNet model,

- The classification report of Precision, Recall, and F-1 Score against each class are stated below:

Table-19: Classification report for DenseNet

Sl. No	**Class**	**Precision**	**Recall**	**F-1 Score**
1	*Alternanthera philoxeroide*	100.00	85.71	92.31
2	*Centella asiatica*	98.78	98.78	98.78
3	*Commelina benghalensis*	97.53	100.00	98.75
4	*Cyperus ochraceus*	100.00	84.38	91.53
5	*Fimbristylis littoralis*	97.22	100.00	98.59
6	*Ipomoea aquatic*	100.00	99.43	99.71
7	*Marsilea minuta*	98.80	98.80	98.80
8	*Panicum repens*	97.10	97.10	97.10
9	*Paspalum scrobiculatum*	98.94	100.00	99.47
10	*Pteris vittata*	100.00	100.00	100.00
11	*Synedrella nodiflora*	94.50	100.00	97.17

- Obtained accuracy of DenseNet model is 98%

- Confusion matrix for DenseNet is stated below:

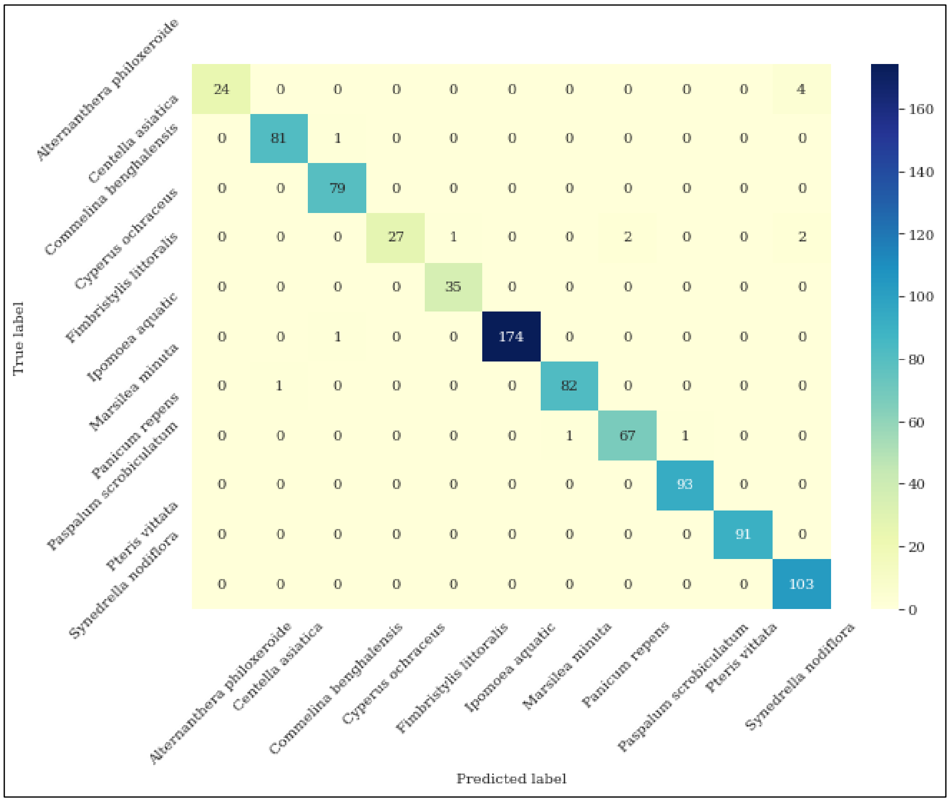

Figure-21: Confusion Matrix for DenseNet

- ROC AUC score of DenseNet is 0.9829 and the corresponding curve is:

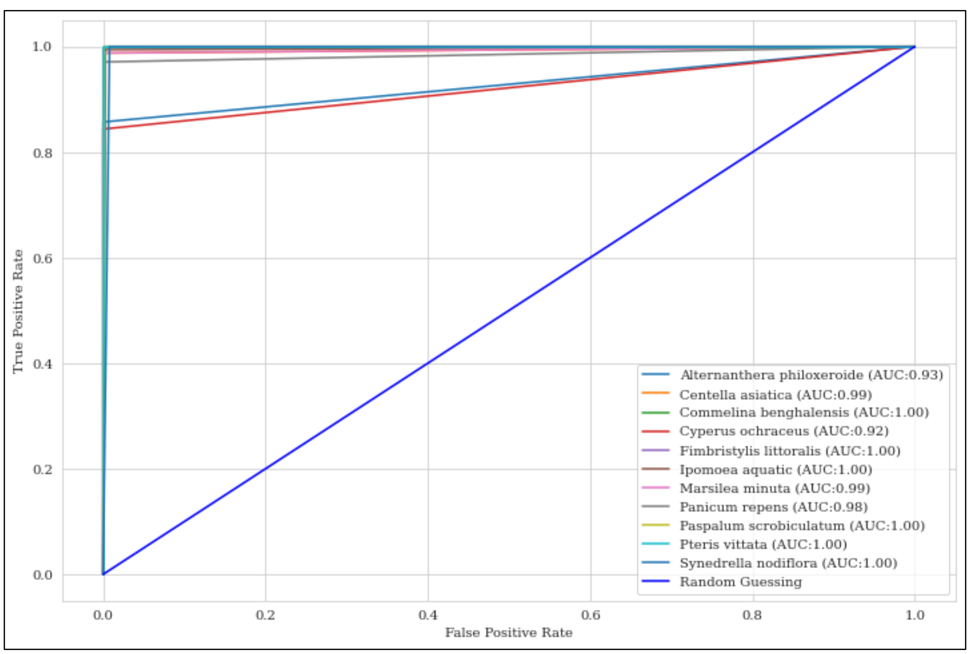

Figure-22: ROC AUC curve for VGG16

Now the models can predict the weeds. Some predictions are stated below where some images are predicted accurately and some are not:

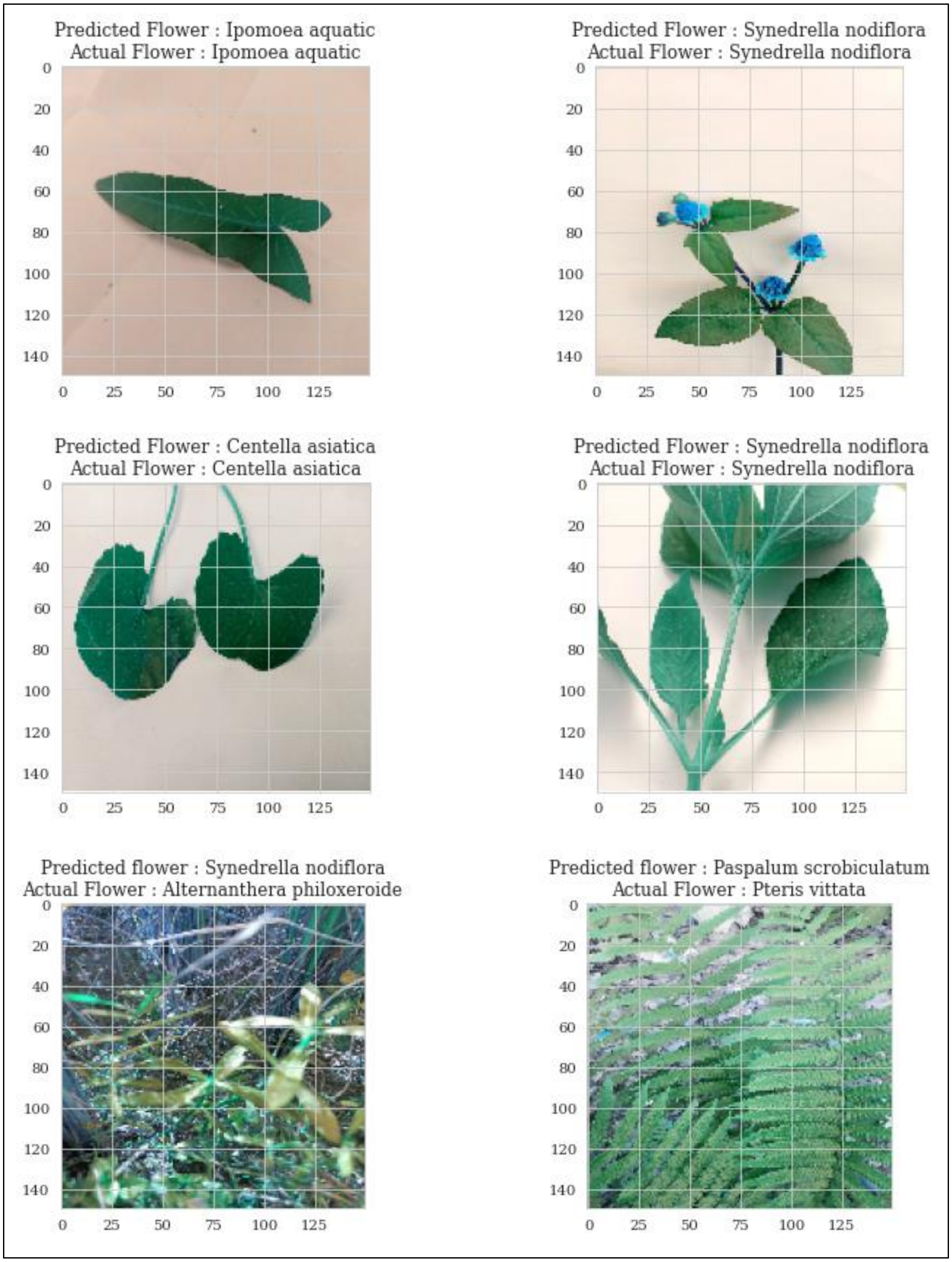

Figure-23: Some sample predictions that our models predicted

4.2 Result Analysis of Mobile App

After developing the app, if the mobile camera was focused on the weeds, it was observed that the app gave 3 possible names of the weeds with the accuracy percentage. The app indicates the name of the weed which has the highest accuracy.

Some screenshot of the app is as follows:

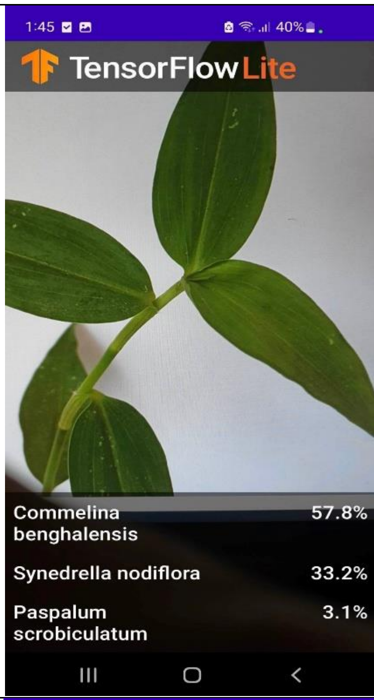

Figure-24: Some example of mobile app weeds detection

Chapter 5

Result Analysis

5.1 Summary

There is no alternative to increasing food production and reducing production costs to meet the food demand of the growing population of Bangladesh. In order to increase food production, especially rice production, effective measures to control production disturbance agents such as weeds are necessary. And if it can be automated, the cost of production can be greatly reduced. In this paper, a system is designed to detect the 11 major weeds of rice fields in Bangladesh based on 4 machine learning algorithms- CNN, VGG16, InceptionV3 and DenseNet. All these algorithms achieved a very high accuracy detecting the weeds. CNN has 87% accuracy, VGG16 achieved 96% accuracy, InceptionV3 showed 93% accuracy and 98% accuracy from DenseNet. These models are trained on a unique dataset of rice fields weeds collected by the authors. Based on this system an android mobile app was developed by which the weeds are detected in real time.

5.2 Future Work

Based on this work the future work can be following:

- A weed killer spray can be set up with a drone and the drone can spray the weeds automatically.
- This system can be applied on other dataset
- Other algorithms can be applied on this dataset

Bibliography

[1] GOODSEEDVENTURES, “Worldwide Food Consumption Per Capita,” *Good Seed Ventures*. https://goodseedventures.com/worldwide-food-consumption-per-capita-2/ (accessed Sep. 02, 2022).

[2] D. Yıldız, “Global Dairy Industry and Trends,” *Feed & Additive Magazine*, May 10, 2021. https://www.feedandadditive.com/global-dairy-industry-and-trends/ (accessed Sep. 02, 2022).

[3] “• Total global rice consumption 2021/22 | Statista.” https://www.statista.com/statistics/255977/total-global-rice-consumption/ (accessed Sep. 02, 2022).

[4] “These are the top 10 countries that produce the most wheat,” *World Economic Forum*. https://www.weforum.org/agenda/2022/08/top-10-countries-produce-most-wheat/ (accessed Sep. 02, 2022).

[5] “Production of wheat worldwide 2021/2022,” *Statista*. https://www.statista.com/statistics/267268/production-of-wheat-worldwide-since-1990/ (accessed Sep. 02, 2022).

[6] S. R., Y. Ashoka, and R. Siva, “EFFECT OF WEEDS AND THEIR MANAGEMENT IN TRANSPLANTED RICE – A REVIEW,” vol. 4, pp. 165–180, Dec. 2016.

[7] J. Mohammed, “What is a Weed?,” *Ministry of Agriculture, Land and Fisheries*, May 13, 2020. https://agriculture.gov.tt/publications/what-is-a-weed/ (accessed Sep. 02, 2022).

[8] B. S. Chauhan, “Grand Challenges in Weed Management,” *Frontiers in Agronomy*, vol. 1, 2020, Accessed: Oct. 19, 2022. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fagro.2019.00003

[9] A. Snir *et al.*, “The Origin of Cultivation and Proto-Weeds, Long Before Neolithic Farming,” *PLoS One*, vol. 10, no. 7, p. e0131422, Jul. 2015, doi: 10.1371/journal.pone.0131422.

[10] “Agriculture, forestry, and fishing, value added (% of GDP) - Bangladesh | Data.” https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS?locations=BD (accessed Sep. 06, 2022).

[11] “Bangladesh - Employment In Agriculture (% Of Total Employment) - 2022 Data 2023 Forecast 1984-2020 Historical.” https://tradingeconomics.com/bangladesh/employment-in-agriculture-percent-of-total-employment-wb-data.html (accessed Sep. 06, 2022).

[12] “Agriculture Growth Reduces Poverty in Bangladesh,” *World Bank*. https://www.worldbank.org/en/news/feature/2016/05/17/bangladeshs-agriculture-a-poverty-reducer-in-need-of-modernization (accessed Sep. 06, 2022).

[13] S. Hassan, “The rice economy,” *The Daily Star*, Jun. 21, 2021. https://www.thedailystar.net/business/economy/news/the-rice-economy-2114957 (accessed Sep. 02, 2022).

[14] daily sun, “Bangladesh ranks 3rd in global rice production | Daily Sun |,” *daily sun*. https://www.daily-sun.com/printversion/details/626049/Bangladesh-ranks-3rd-in-global-rice-production (accessed Nov. 18, 2022).

[15] “Paspalum scrobiculatum L. | Species,” *WIKTROP - Weed Identification and Knowledge in the Tropical and Mediterranean areas*. https://portal.wiktrop.org/species/show/241 (accessed Sep. 08, 2022).

[16] “*Paspalum scrobiculatum*,” *Wikipedia*. Aug. 21, 2022. Accessed: Sep. 07, 2022. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Paspalum_scrobiculatum&oldid=1105687805

[17] “Ipomoea aquatica Forssk. | Species,” *WIKTROP - Weed Identification and Knowledge in the Tropical and Mediterranean areas*. https://portal.wiktrop.org/species/show/167 (accessed Dec. 13, 2022).
[18] “*Ipomoea aquatica*,” *Wikipedia*. Dec. 03, 2022. Accessed: Dec. 13, 2022. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Ipomoea_aquatica&oldid=1125277514
[19] “Cyperus iria L. | Species,” *WIKTROP - Weed Identification and Knowledge in the Tropical and Mediterranean areas*. https://portal.wiktrop.org/species/show/97 (accessed Sep. 08, 2022).
[20] B. S. Chauhan and D. E. Johnson, “Ecological studies on *Cyperus difformis* , *Cyperus iria* and *Fimbristylis miliacea* : three troublesome annual sedge weeds of rice,” *Annals of Applied Biology*, vol. 155, no. 1, pp. 103–112, Aug. 2009, doi: 10.1111/j.1744-7348.2009.00325.x.
[21] M. A. Alam, M. A. Hakim, A. S. Juraimi, M. Y. Rafii, M. M. Hasan, and F. Aslani, “Potential allelopathic effects of rice plant aqueous extracts on germination and seedling growth of some rice field common weeds,” *Italian Journal of Agronomy*, vol. 13, no. 2, Art. no. 2, Mar. 2018, doi: 10.4081/ija.2018.1066.
[22] “Centella asiatica (L.) Urb. | Species,” *WIKTROP - Weed Identification and Knowledge in the Tropical and Mediterranean areas*. https://portal.wiktrop.org/species/show/55 (accessed Sep. 08, 2022).
[23] “Pennywort.,” *Weed Identification – Brisbane City Council*. https://weeds.brisbane.qld.gov.au/weeds/pennywort (accessed Sep. 08, 2022).
[24] Y. Kosaka, L. Xayvongsa, A. Vilayphone, H. Chanthavong, S. Takeda, and M. Kato, “Wild Edible Herbs in Paddy Fields and Their Sale in a Mixture in Houaphan Province, the Lao People’s Democratic Republic,” *Econ Bot*, vol. 67, no. 4, pp. 335–349, Dec. 2013, doi: 10.1007/s12231-013-9251-6.
[25] “*Panicum repens*,” *Wikipedia*. Mar. 09, 2022. Accessed: Sep. 08, 2022. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Panicum_repens&oldid=1076206353
[26] “Panicum repens L. | Species,” *WIKTROP - Weed Identification and Knowledge in the Tropical and Mediterranean areas*. https://portal.wiktrop.org/species/show/234 (accessed Sep. 08, 2022).
[27] “*Marsilea minuta*,” *Wikipedia*. Feb. 06, 2022. Accessed: Oct. 20, 2022. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Marsilea_minuta&oldid=1070258648
[28] “Marsilea minuta L. | Species,” *WIKTROP - Weed Identification and Knowledge in the Tropical and Mediterranean areas*. https://portal.wiktrop.org/species/show/204 (accessed Oct. 20, 2022).
[29] “Alternanthera philoxeroides (Mart.) Griseb. | Species,” *WIKTROP - Weed Identification and Knowledge in the Tropical and Mediterranean areas*. https://portal.wiktrop.org/species/show/16 (accessed Dec. 13, 2022).
[30] “*Synedrella*,” *Wikipedia*. Nov. 04, 2022. Accessed: Dec. 13, 2022. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Synedrella&oldid=1119936892
[31] “Synedrella nodiflora (L.) Gaertn. | Species,” *WIKTROP - Weed Identification and Knowledge in the Tropical and Mediterranean areas*. https://portal.wiktrop.org/species/show/320 (accessed Dec. 13, 2022).
[32] “*Fimbristylis littoralis*,” *Wikipedia*. Jun. 13, 2022. Accessed: Sep. 23, 2022. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Fimbristylis_littoralis&oldid=1092987952
[33] “Fimbristylis littoralis (lesser fimbristylis).” https://www.cabi.org/isc/datasheet/24023 (accessed Sep. 23, 2022).
[34] “Fimbristylis littoralis Gaudich. | Species.” https://portal.wiktrop.org/species/show/142 (accessed Sep. 23, 2022).

[35] "Commelina benghalensis L. | Species," *WIKTROP - Weed Identification and Knowledge in the Tropical and Mediterranean areas*. https://portal.wiktrop.org/species/show/71 (accessed Dec. 13, 2022).
[36] "*Pteris vittata*," *Wikipedia*. May 25, 2022. Accessed: Dec. 13, 2022. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Pteris_vittata&oldid=1089678327
[37] M. Kashem, M. A. A. Faroque, and S. Bilkis, "Weed Management in Bangladesh: Policy Issues to Better Way Out," *Journal of Science Foundation*, vol. 7(2), pp. 59–67, Jan. 2009.
[38] M. K. Upadhyaya and R. E. Blackshaw, Eds., *Non-chemical weed management: principles, concepts and technology*. Wallingford, UK ; Cambridge, MA: CABI, 2007.
[39] M. Hasanuzzaman, "Identification of Some Common Herbicides and Study of their Physical Properties," p. 2, 2015.
[40] S. Kaur and S. Singh, "Bio-efficacy of different herbicides for weed control in direct-seeded rice," p. 4.
[41] A. Wang, W. Zhang, and X. Wei, "A review on weed detection using ground-based machine vision and image processing techniques," *Computers and Electronics in Agriculture*, vol. 158, pp. 226–240, Mar. 2019, doi: 10.1016/j.compag.2019.02.005.
[42] X. Zhao, X. Wang, C. Li, H. Fu, S. Yang, and C. Zhai, "Cabbage and Weed Identification Based on Machine Learning and Target Spraying System Design," *Frontiers in Plant Science*, vol. 13, 2022, Accessed: Oct. 05, 2022. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fpls.2022.924973
[43] N. Islam *et al.*, "Early Weed Detection Using Image Processing and Machine Learning Techniques in an Australian Chilli Farm," *Agriculture*, vol. 11, no. 5, Art. no. 5, May 2021, doi: 10.3390/agriculture11050387.
[44] S. Badhan, K. Desai, M. Dsilva, R. Sonkusare, and S. Weakey, "Real-Time Weed Detection using Machine Learning and Stereo-Vision," in *2021 6th International Conference for Convergence in Technology (I2CT)*, Apr. 2021, pp. 1–5. doi: 10.1109/I2CT51068.2021.9417989.
[45] Y. Shendryk, N. A. Rossiter-Rachor, S. A. Setterfield, and S. R. Levick, "Leveraging High-Resolution Satellite Imagery and Gradient Boosting for Invasive Weed Mapping," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 13, pp. 4443–4450, 2020, doi: 10.1109/JSTARS.2020.3013663.
[46] O. Barrero, D. Rojas, C. Gonzalez, and S. Perdomo, "Weed detection in rice fields using aerial images and neural networks," in *2016 XXI Symposium on Signal Processing, Images and Artificial Vision (STSIVA)*, Aug. 2016, pp. 1–4. doi: 10.1109/STSIVA.2016.7743317.
[47] F. Dankhara, K. Patel, and N. Doshi, "Analysis of robust weed detection techniques based on the Internet of Things (IoT)," *Procedia Computer Science*, vol. 160, pp. 696–701, Jan. 2019, doi: 10.1016/j.procs.2019.11.025.
[48] S. Kulkarni and D. S. A. Angadi, "IOT BASED WEED DETECTION USING IMAGE PROCESSING AND CNN," vol. 4, no. 3, p. 4, 2019.
[49] Prabhu, "Understanding of Convolutional Neural Network (CNN) — Deep Learning," *Medium*, Nov. 21, 2019. https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148 (accessed Sep. 25, 2022).
[50] Geoffrey, "Deep learning — Activation Function," *Medium*, Aug. 31, 2022. https://towardsaws.com/activation-function-f76bfc03e215 (accessed Sep. 25, 2022).
[51] J. Brownlee, "How to Choose an Activation Function for Deep Learning," *MachineLearningMastery.com*, Jan. 17, 2021. https://machinelearningmastery.com/choose-an-activation-function-for-deep-learning/ (accessed Feb. 06, 2023).

[52] "What is Gradient Descent?," Oct. 28, 2020. https://www.ibm.com/cloud/learn/gradient-descent (accessed Oct. 21, 2022).
[53] R. Kwiatkowski, "Gradient Descent Algorithm — a deep dive," *Medium*, Jul. 13, 2022. https://towardsdatascience.com/gradient-descent-algorithm-a-deep-dive-cf04e8115f21 (accessed Oct. 21, 2022).
[54] "Gradient Descent in Machine Learning - Javatpoint." https://www.javatpoint.com/gradient-descent-in-machine-learning (accessed Oct. 21, 2022).
[55] "ML | Stochastic Gradient Descent (SGD)," *GeeksforGeeks*, Feb. 15, 2019. https://www.geeksforgeeks.org/ml-stochastic-gradient-descent-sgd/ (accessed Oct. 21, 2022).
[56] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition." arXiv, Apr. 10, 2015. doi: 10.48550/arXiv.1409.1556.
[57] G. Learning, "Everything you need to know about VGG16," *Medium*, Sep. 23, 2021. https://medium.com/@mygreatlearning/everything-you-need-to-know-about-vgg16-7315defb5918 (accessed Feb. 09, 2023).
[58] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision." arXiv, Dec. 11, 2015. Accessed: Feb. 06, 2023. [Online]. Available: http://arxiv.org/abs/1512.00567
[59] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, Jul. 2017, pp. 2261–2269. doi: 10.1109/CVPR.2017.243.

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[Ref*] AKM Saiful Islam, Md Anwar Hossen, Md Khairul Alam Bhuiyan, Md Monirul Islam, Muhammad Abdur Rahman 2017: Weed Management in Mechanically Transplanted Rice. Publication number 224, Bangladesh Rice Research Institute, Gazipur, Bangladesh.

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