Bioelectricity Generation Using Algal Fuel Cells: A Machine Learning Approach

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Abstract*– Microalgae are regarded as one of the most promising and futuristic solutions for green and sustainable generation of bioelectricity. In this study, machine learning (ML) algorithms were applied on a constructed dataset of 648 data points to predict optimal cultivation parameters required for achieving high microalgal biomass concentration, which is a critical factor for algal fuel cell (AFC) efficiency. Upon implementation of decision tree (DT) algorithm, results showed significant classification for microalgal biomass concentration in relation to target microalgal parameters. Microalgal biomass concentrations were recorded at highest values when microalgae were Monoraphidium and Nannochloropsis. N and light levels were also contributing factors to biomass concentration. Bio-oil was at its highest values when pH at was high at ≥7.1 and microalgae were Chlorella, Desmodesmus, and Monoraphidium. Also, light, K, and biomass concentration were contributing factors for enhancing bio-oil content. Microalgal samples of Chlamydomonas, Desmodesmus, Monoraphidium and Scenedesmus required average light intensity levels to achieve their highest bio-oil content. Temperature at 27 °C was efficient for Chlorella, Ettlia, Monoraphidium and Nannochloropsis samples to achieve high biomass concentrations. pH levels were recorded optimal when microalgal bio-oil content was at highest levels ≥21 %w/w. Prediction levels were validated using RMSE and R^2 and both showed accurate results using generated decision trees from assigned data partitions.

1. INTRODUCTION

As energy consumption reports show exceedingly high levels of usage in industrialized nations, this has caused great impact on greenhouse gas emissions due to the use of fuels sourced of petroleum origins. Currently, most of the energy utilized for daily tasks is non-renewable or derived from fossil fuels (1). To meet the high energy needs of continued industrialization, economic expansion, and expanding populations, fossil fuels including carbon, natural gas, and petroleum are frequently employed in the transportation and energy sectors. Due to thermal expansion and warmer sea surfaces brought on by the greenhouse effect, glaciers and ice sheets may collapse, raising sea levels and indirectly affecting the environment (2). Bioenergy is a class of renewable energy that is generated from biological sources, where biomass is either utilized as fuels directly or transformed into liquid or gas form. Forest trees, agricultural forest wastes, crops, and aquatic plants are among the primary biomass types utilized to produce bioenergy. Biofuels are subject to extensive research since they are renewable, clean, and good for the environment (Fig 1). Biohydrogen, bioethanol, and biodiesel make up the majority of biofuels and are created via a variety of methods, including transesterification, fermentation, and gasification (2). Bioelectricity is a sustainable form of electricity produced from renewable source of energy, particularly through utilization of algal fuel cells (AFCs) (3). Large groupings of aquatic photosynthetic creatures called algae are divided into two subgroups: macroalgae and microalgae, which might have one cell or many. Like terrestrial plants, both microalgae and macroalgae use chlorophyll as their primary photosynthetic pigment to fix atmospheric CO2 through photosynthesis (4).

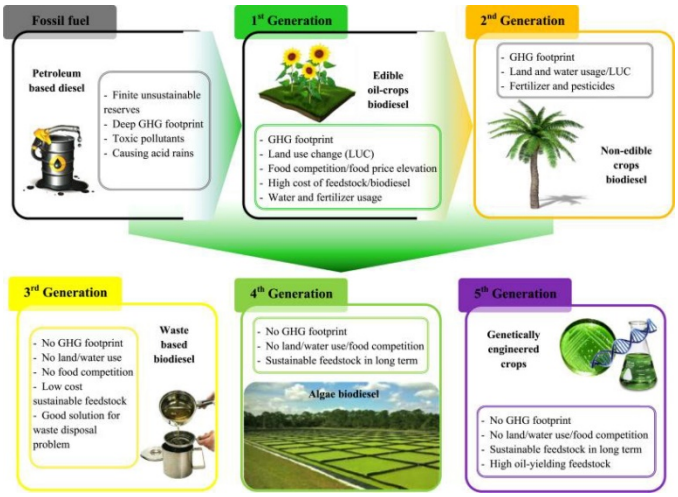

Fig 1. Bioenergy generations as replacement for fossil fuels. Retrieved from (5)

There are many different ecosystems where algae can be found, including the ocean for marine algae and rivers, lakes, ponds, and reservoirs for freshwater algae. Algal growth is highly influenced by the temperature of the environment, the

quantity of sunlight, and nutrients. Algal biomass has a wide range of advantageous chemicals that have use in several industries. Moreover, the benefit of using algae as a feedstock for the manufacture of biofuel primarily depends on the algae's high productivity (6). Algae may complete a life cycle in a few days and develop far faster than terrestrial plants (2, 7). Studies that seek the development of energy sources which focus on the replacement of unrenewable energy sources to limit the greenhouse gases emissions, brought out to light the algal fuel cell (AFC) that generate convert the chemical reactions energy to electrical energy using redox reaction (7). AFC basically consists of anode where the oxidation reaction takes place, cathode where the reduction reaction occurs, and an electrical wire that allow electron transfer. In the early 2000s, new studies tended to enhance biofuel cells by using algae to assist at the reaction at the cathode to function the wastewater treatment and the production of electricity, to be algae fuel cell (AFC) in order to reduce the operation cost as the algae produces oxygen by photosynthesis. At the anodic chamber of the AFC the bacteria decompose the organic matter that is fed to the fuel cell by oxidation reaction where the reaction products are electrons and carbon dioxide, and on the cathodic chamber electron acceptor works by reduction (7, 8), the algae can be used in cathodic chamber only or in both cathodic and anodic chambers to function as half-cell anode in the full algal fuel cell (8) (Fig 2).

The advantages of microalgae in fuel cell research boils down to decreasing the operation cost as the cathodic reaction needs to be oxygenated enough in order for the reaction to take place so in the ordinary biofuel cell a sparger must be attached in order to provide the cathodic chamber with oxygen, however using an algae biofilm can replace the sparger as it naturally produce oxygen by photosynthesis to enhance the efficiency of the redox reaction (7). Using AFCs also allow to harvest the excess algae growing in the chamber to be used as biofuel (3).

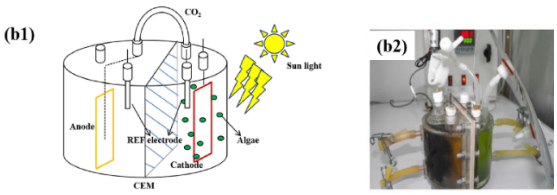

Fig 2. Algal fuel cell setup for bioelectricity generation Retrieved from (9)

In this study, investigation of optimal parameters required for achieving efficient cultivation levels of microalgae are assessed using machine learning algorithms across a constructed microalgal dataset through targeting high microalgal biomass concentrations and several essential parameters, which will have a profound impact on algal fuel cells efficiency towards high bioelectricity generation levels.

2. METHODOLOGY

A dataset of 648 data points and 72 data entries was created following data mining for algal cultivation parameters, biomass concentration, and bio-oil content from multiple research publications. The final dataset included 9 variables including microalgal type/class, as these parameters were proven critical for algal growth conditions across all species.

The variables used in this research are classified as follows based on assigned data type:

1- Categorical data (Class: *Chlorella* "C", *Chlamydomonas* "CS", *Desmodesmus* "D", *Ettlia* "E", *Monoraphidium* "M", *Nannochloropsis* "N", and *Scenedesmus* "S").
2- Numerical data (Biomass concentration ($g.L^{-1}$), Bio-oil content (%w/w), light ($\mu mol.m^{-2}.s^{-1}$), temperature (°C), N ($g.L^{-1}$), K ($g.L^{-1}$), P ($g.L^{-1}$), and pH).

Machine learning was applied using decision tree (DT) algorithm. R programming language (R.4.0) was used, while "rpart", "mlbench", "DAAG", "party", "rattle" , "caret", "ggplot2", and "Metrics" were among the used R packages. Factors were assigned to microalgal strain classes before creating both training and testing data partitions.

Training and testing were performed following (80%) and (20%) percentages of original dataset were randomly outlined respectively. Classification was calculated using Gini diversity index where p_i was assigned for biomass concentration, bio-oil content, light, temperature and pH parameters respectively.

$$Gini(t) = 1 - \sum_{i=1}^{j} P(i|t)^2$$

During decision tree construction, minimum root node was assigned to default as (minBucket=1), while maximum depth was counted as (maxdepth=4). Then the decision tree was plotted using "rpart.plot" while complexity parameters were printed to provide general root and child nodes information. Next, prediction of biomass concentration, bio-oil content, light, temperature and pH were done following tree construction from training data partition. Finally, root mean square error (RMSE) and R squared (R^2) values were calculated to assess the validity of each constructed decision tree.

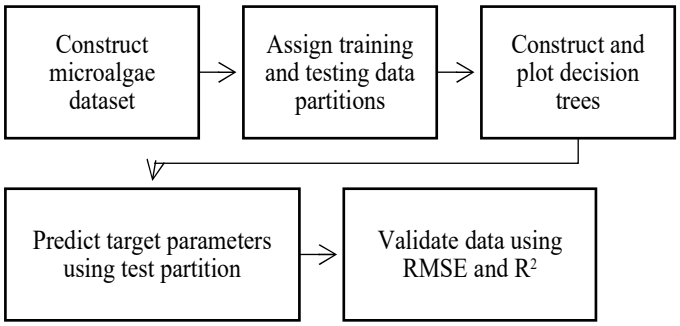

Fig 3. Workflow of Decision Tree (DT) algorithm

The data used in this study was extracted from Elsevier, Springer, and Wiley databases based on microalgal cultivation, bioenergy, and algal fuel cell research publications (10-20).

```r
# Bioelectricity Generation Using Algal Fuel Cells: A Machine Learning Approach

# Loading required libraries
library(rpart)
library(mlbench)
library(DAAG)
library(tree)
library(Metrics)
library(ggplot2)
library(rpart.plot)
library(party)
library(caret)
library(rattle)

# Reading constructed microalgae dataset
data <- read.csv("E:/Data.csv")

# Assigning factor for microalgal class
data$Class <- factor(data$Class)

# Get structure of data
str(data)

# Assigning training and testing data partitions
pd <- sample(2, nrow(data), replace = T, prob = c(0.8, 0.2))
train <- data[pd == 1,]
test <- data[pd == 2,]

# Training and plotting data for detecting optimized biomass concentration
# Using decision tree (DT) algorithm
set.seed(1000)
tree_biomass <- rpart(formula = Biomass ~ .,
                      data = train,
                      control = list(minbucket=2, maxdepth=4),
                      method = "anova"
                      )
rpart.plot(tree_biomass, box.palette="RdBu", shadow.col="gray", nn=TRUE)
printcp(tree_biomass)
rpart.rules(tree_biomass)

# Training and plotting data for detecting optimized bio-oil content
# Using decision tree (DT) algorithm
set.seed(1000)
tree_bio_oil <- rpart(formula = Bio_oil ~ .,
                      data = train,
                      control = list(minbucket=1, maxdepth=4),
                      method = "anova"
                      )
rpart.plot(tree_bio_oil, box.palette="RdBu", shadow.col="gray", nn=TRUE)
printcp(tree_bio_oil)
rpart.rules(tree_bio_oil)

# Training and plotting data for detecting optimized light conditions
# Using decision tree (DT) algorithm
set.seed(1000)
tree_light <- rpart(formula = Light ~ .,
                    data = train,
                    control = list(minbucket=1, maxdepth=4),
                    method = "anova"
                    )
rpart.plot(tree_light, box.palette="RdBu", shadow.col="gray", nn=TRUE)
printcp(tree_light)
rpart.rules(tree_light)

# Training and plotting data for detecting optimized Temperature conditions
# Using decision tree (DT) algorithm
set.seed(1000)
tree_temp <- rpart(formula = Temp ~ .,
                   data = train,
                   control = list(minbucket=1, maxdepth=4),
                   method = "anova"
                   )
rpart.plot(tree_temp, box.palette="RdBu", shadow.col="gray", nn=TRUE)
printcp(tree_temp)
rpart.rules(tree_temp)

# Training and plotting data for detecting optimized pH conditions
# Using decision tree (DT) algorithm
set.seed(1000)
tree_pH <- rpart(formula = pH ~ .,
                 data = train,
                 control = list(minbucket=1, maxdepth=4),
                 method = "anova"
                 )
rpart.plot(tree_pH, box.palette="RdBu", shadow.col="gray", nn=TRUE)
printcp(tree_pH)
rpart.rules(tree_pH)

# Predicting optimized biomass concentration and microalgal parameters
# using testing data partition
predict_biomass <- rpart.predict(tree_biomass, train)
predict_bio_oil <- rpart.predict(tree_bio_oil, train)
predict_light <- rpart.predict(tree_light, train)
predict_temp <- rpart.predict(tree_temp, train)
predict_pH <- rpart.predict(tree_pH, train)

# Obtaining Root Mean Square Error for predicted conditions/parameters
sqrt(mean((train$Biomass - predict_biomass)^2))
sqrt(mean((train$Bio_oil - predict_bio_oil)^2))
sqrt(mean((train$Light - predict_light)^2))
sqrt(mean((train$Temp - predict_temp)^2))
sqrt(mean((train$pH - predict_pH)^2))

# Obtaining R-squared values for predicted conditions/parameters
(cor(train$Biomass,predict_biomass))^2
(cor(train$Bio_oil,predict_bio_oil))^2
(cor(train$Light,predict_light))^2
(cor(train$Temp,predict_temp))^2
(cor(train$pH,predict_pH))^2
```

Fig 4. R script of Decision Tree (DT) algorithm implementation for prediction of optimal microalgal conditions/parameters

3. Results & Discussion

Decision tree (DT) algorithm was implemented on constructed microalgal dataset to determine the most efficient

cultivation parameters for achieving high biomass concentration. Upon calculation of Gini's diversity index for training data, constructed DT showed that parent node (100% of data) pertaining biomass concentration as feature (1.4 $g.L^{-1}$) was further classified based on N, microalgal strain class, and light conditions. If N level was high (≥1.2 $g.L^{-1}$), then the tree further dissipates towards less efficient biomass concentration levels. Samples at this level have 0.48 $g.L^{-1}$ of biomass concentration or less and contributes to 50% of training data. Further, if the strain samples were *Monoraphidium* and *Scenedesmus*, then the biomass concentration will be 25% of data at 0.11 $g.L^{-1}$ while for other classes it will be 25% of data as well and achieve biomass conc. at 0.85 $g.L^{-1}$. However, for the left node branching with lower N levels, for *Chlorella*, *Chlamydomonas*, *Desmodesmus*, *Ettlia*, *Monoraphidium,* or *Scenedesmus* (2.3 $g.L^{-1}$ at 50% of data), light parameter is quite essential for further branching where samples with light ≥ 118 $\mu mol.m^{-2}.s^{-1}$ the samples will have 1.5 $g.L^{-1}$ at 1.5% of data, however child node branching for lower light intensities reach further classification of strain classes where *Chlamydomonas* and *Ettlia* samples have 1.4 $g.L^{-1}$ at 3% of data while other classes have 2.5 $g.L^{-1}$ at 33% of data, finally *Monoraphidium* and *Nannochloropsis* samples had the highest recorded biomass concentration levels 3.9 $g.L^{-1}$ at 3.9% of data (Fig 5).

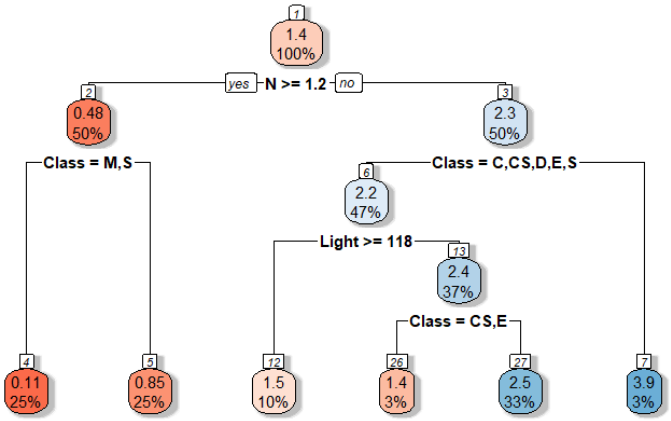

Fig 5. Decision tree classification for achieving optimal microalgal biomass concentration

Next, decision tree was also implemented for assessing optimum bio-oil content in microalgal samples using tuned growth conditions. Upon calculation of Gini index for training data, obtained tree showed that parent node (100% of data) pertaining bio-oil contents as feature (25 %w/w) was further classified based on microalgal class, light and pH conditions. If the microalgal samples were of *Desmodesmus*, *Ettlia, Nannochloropsis and Scenedesmus* origin, then they are further classified based on light and pH. Then if light was ≥340 $\mu mol.m^{-2}.s^{-1}$ then the bio-oil content will be 9.5 %w/w, however left branching divides based on K levels into 17 %w/w (3%) and then further dissipates based on biomass concentration if <3.5 $g.L^{-1}$ to 23 %w/w and for samples with higher levels, it reaches 31 %w/w. Left leaf node then branches based on pH of ≥7.1 to 25 %w/w (12%) or 32 %w/w for lower pH (Fig 6). Samples of *Chlorella*, *Desmodesmus*, and *Monoraphidium* tends to have the highest bio-oil content when pH was ≥7.1.

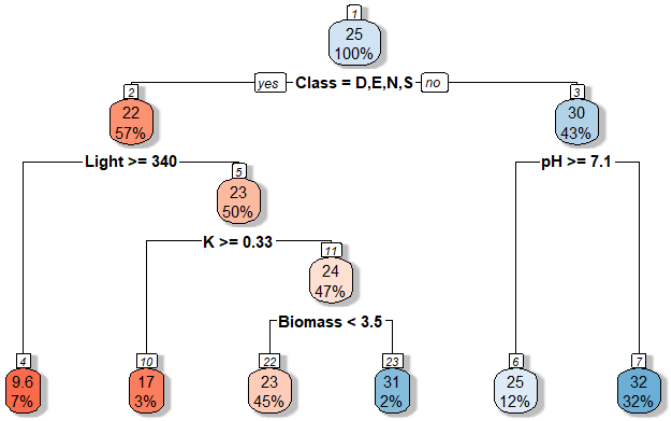

Fig 6. Decision tree classification for achieving optimal microalgal bio-oil content

Also, following light DT construction, bio-oil was the main contributing factor for optimal light conditions, where samples with ≥13 %w/w levels required the most illumination (550 $\mu mol.m^{-2}.s^{-1}$ at 7% of data), while samples with increasing levels of bio-oil content <32 %w/w required lower light intensities at 240 $\mu mol.m^{-2}.s^{-1}$, then samples of several microalgal classes including *Chlamydomonas*, *Desmodesmus*, *Monoraphidium and Scenedesmus* required lowest light intensity at 76 $\mu mol.m^{-2}.s^{-1}$ while other microalgal strains required light with a range of 119 $\mu mol.m^{-2}.s^{-1}$ (Fig 7).

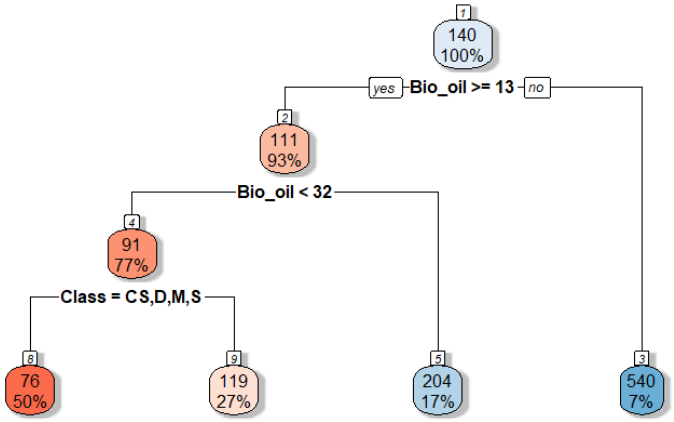

Fig 7. Decision tree classification for achieving optimal light conditions

Then, decision tree was constructed for microalgal training samples to detect optimal temperature. Results showed that parent node for samples of class *Chlorella, Ettlia*, *Monoraphidium and Nannochloropsis* had their temperature at 26 °C (45%) with further branching based on biomass levels at <0.97 %w/w for 25 °C (18%) while samples of same class

but with higher biomass levels had temperature at 27 °C. However samples with other classes were branched based on N concentration to ≥1.3 $g.L^{-1}$ where samples had temperature of 27 °C (20%) and at 28 °C (35%) for samples with higher N levels.

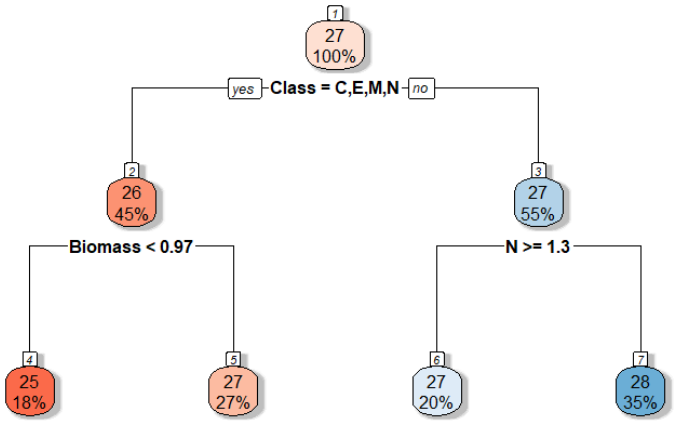

Fig 8. Decision tree classification for achieving optimal microalgal temperature

Furthermore, pH decision tree showed that bio-oil was also a major factor for optimal pH determination. As bio-oil level of ≥21%w/w had regular pH level of 7.5 (10%) while lower bio-oil content in microalgal samples were classified based on N concentration of <2.8 to pH of 6.4 $g.L^{-1}$ (5%) while bio-oil content for samples <18 %w/w had lowest pH at 6.4 (Fig 9).

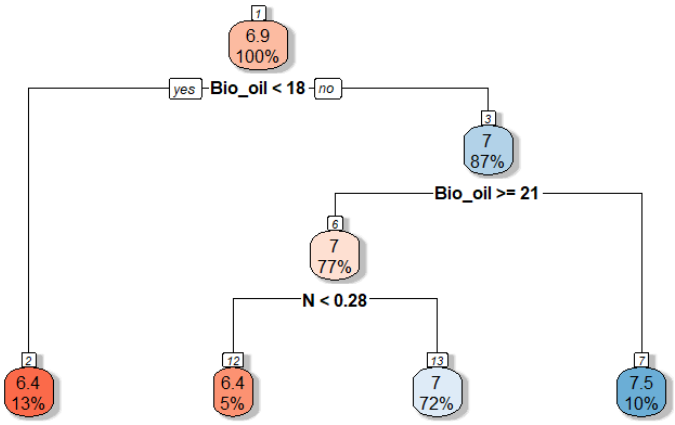

Fig 9. Decision tree classification for achieving optimal microalgal pH

Next, prediction of microalgal biomass levels and targeted parameters were performed using (rpart.prediction) function based on generated decision trees. Results showed that root mean square error and r-squared levels for testing data partition showed acceptable levels for both biomass concentration and lipid contents from microalgal data, where biomass concentration achieved (0.46, 0.83) in former validation tests respectively, while bio-oil content achieved (5.40, 0.55). Other microalgal parameters had the following results; light (48.7, 0.85), temperature (1.40, 0.34) and pH (0.33, 0.46) (Table 1).

RMSE was reported to be better in biomass concentration, temperature and pH prediction than bio-oil content and light. However, this can be attributed to already high data input levels and low variability compared to other parameters in the collected microalgae dataset. Such results indicate that both validation tests were performed correctly, and that each parameter can be used effectively through the generated decision trees to classify microalgal samples for achieving high biomass concentration levels, thus increasing the efficacy of algal fuel cells for bioelectricity generation.

Condition/Parameter	RMSE	R^2
Biomass concentration	0.46	0.83
Bio-oil content	5.40	0.55
Light	48.7	0.85
Temperature	1.40	0.34
pH	0.33	0.46

Table 1. Root mean square error and R-squared values for predicted outcomes in testing microalgal data

Algae growth requirements:

The choice of an appropriate nutrient media is one of the main goals in generating goods from algae. The chemical makeup of the medium is one of the main variables influencing the choice of medium. When the conditions for growth are met, the biomass's output can be raised. Regarding growth requirements, CO2 transfer, nutrient availability, light, and temperature are the most crucial variables. According to some experts, agitation, mixing, and pH all have an impact on how quickly algae develop. These elements may alter metabolism, which could have an impact on microalgae development and biomass composition (4).

1. Inorganic carbon dioxide:

About 0.0383 percent of the air's volume is made up of CO2. Climate change, sea level rise, and species survival will all be impacted when atmospheric CO2 concentrations reach extremely high (hazardous levels). Higher than acceptable CO2 levels will harm green plants and make people feel lightheaded and uncoordinated. Like other terrestrial plants, algae use CO2 as a source of carbon. Flue gas CO2 can also be utilized as a supply of CO2 for growing microalgae, which can help to lessen air pollution. Low levels of CO2 from the air are absorbed by water, which has an impact on biomass growth. Growth and algal production in intense algae cultivation systems will be constrained and slowed down by a lack of or insufficient CO2 (2). The concentration of CO2 available affects CO2 fixation in photosynthesis during algal development. Microalgae should be able to exploit the CO2 absorbed if it is present in the water. Desorption can also occur

if the atmospheric CO2 that has been absorbed is returned. By employing a packed bed or a bubbling effect, the zone of interaction can be expanded (4).

2. Nutrients required for growth:

For maintaining good algal growth, the delivery of nutrients and other growth requirements to algae cultures is crucial and extremely significant. The most prevalent nutrients are heavy metals, organic carbon (C), nitrogen (N), and phosphorus (P). Compared to microalgae, large, long-living macroalgae have lower nutrient needs because of their slower development rates. The composition of lipids and fatty acids within algal cells will alter as a result of variations in nutrition availability, in addition to having an impact on cell size. According to a prior study, one of the most often applied strategies to increase microalgal triacylglycerol (TAG) synthesis is food starvation. The rate of algal cellular division will slow down in nutrient shortages (3, 4).

3. Light

Algae are typically phototrophic and autotrophic creatures, meaning they need light to perform photosynthesis. The cells of autotrophic organisms have pigment molecules called chlorophyll that are specialized for absorbing a certain color of light. The amount of pigment in algae will impact how well they can absorb light energy and transform it into the right amount of chemical energy (4).

4. Temperature

66-70% of microalgae are made of unsaturated fatty acids and 29-33% saturated fatty acids, which makes temperature a significant environmental factor in determining the size of the cell, lipid concentration, and fatty acid makeup inside the cell Compared to 25^{o}C, the amount of saturated fatty acids increases at 35^{o}C (30 % and 34% respectively). This implies that as temperature rises, saturated fatty acid concentration and algal growth rate both increase until the ideal temperature is attained. The growth rate will slow as the temperature rises further. Algal cultures that are overheated witness a sharp drop in growth rate as a result (4, 6).

5. pH

In addition to having an impact on growth and the amount of carbon available for algal photosynthesis, pH fluctuations in the medium have been found to influence the makeup of certain lipids. Variations in pH may have a direct physiological impact by altering the distribution of CO2 absorption or the availability of trace metals and vital nutrients (4, 20).

6. Aeration, mixing, and turbulence

To increase growth and biomass output as well as biochemical composition, aeration is crucial in algal cultivation. Aeration can be given to the algal cultures to eliminate shadowing issues brought on by a high particle concentration. All cells in the culture are subjected to light by mixing it, even for a brief time. Bubbles of air can be produced from the bottom of tubes to mix small-scale cultures. Jet pumps or paddle wheels are typically used to mix large-scale outdoor environments, such as ponds, resulting in turbulent flow close to the wheels and laminar flow downstream (4).

Photobioreactors

In East Europe, Israel, and Japan, commercial manufacturing of algae began between the early and late 1970s. Algae were produced for profit in open ponds during this time as a nutritious food. For the inhabitants of those regions in Africa, Lake Chad and Lake Texcoco served as the primary sources of spirulina biomass. In actuality, the reason for cultivating algae relied on the requirements of the people. Algal pond systems for water treatment were created in the US. Artificial light, solar light, or a combination of both can be used to illuminate algal cultivation systems. Included among naturally lighted algal culture systems with substantial illumination surface areas are open ponds, flat-plate, horizontal/serpentine tubular airlift, and inclined tubular photobioreactors. These photobioreactors include the following: conical, stirred-tank, helical tube, bubble column, and airlift column, and seaweed type photobioreactors (4, 21).

1. Open ponds

Open ponds can be divided into two categories: naturally occurring waterways (lakes, lagoons, and ponds) and manufactured ponds or containers. Systems like shallow huge ponds, tanks, circular ponds, and raceway ponds are the most frequently employed ones. Open ponds have the advantage of being simpler to build and maintain than most closed systems, which is one of its main benefits. Much effort is now being paid to the development of suitable closed systems, such as flat-plate, tubular, vertical-column, and internally illuminated photobioreactors, to address the issues with open ponds (11).

2. Flat plate

Due to their substantial illumination surface area, flat plate photobioreactors have attracted a lot of interest for the culture of photosynthetic microorganisms. Flat plate photobioreactors are often constructed of transparent materials to maximize the use of solar light energy. In comparison to horizontal tubular photobioreactors, the accumulation of dissolved oxygen concentrations in flat plate photobioreactors is comparatively low (11).

3. Tubular bioreactor:

One of the best forms of photobioreactors for outdoor mass cultures is the tubular one. The majority of outdoor tubular photobioreactors are typically made of glass or plastic tubes, and the cultures are often circulated using an airlift system rather than a pump. They can take the shape of a vertical, near-horizontal, conical, inclined, or horizontal/serpentine photobioreactor (11).

Fig 8. Photobioreactors used for microalgal cultivation Retrieved from (21)

4. vertical column

The monoseptic operation of vertical-column photobioreactors is simple, inexpensive, and compact. They also hold great promise for the large-scale growth of algae. Certain bubble column photobioreactors have draught tubes or are made of split cylinders, or both. Intermixing between the riser and the downcomer zones of the photobioreactor happens in draught tube photobioreactors through the walls of the draught tube (11).

5. Stirred tank photobioreactor

The most common type of reactor is the stirred tank reactor, where agitation is given mechanically with the aid of impellers that come in various sizes and forms. Baffles are used to lessen vortexing. At the bottom, CO2 enriched air is bubbled to give algae with a carbon source for growth. The main drawback of this technology is the low surface area to volume ratio, which lowers light harvesting effectiveness. This type of bioreactor has been converted into a photobioreactor by external illumination with fluorescent lights or optical fibers. Although optical fibers have been used, doing so for illumination has significant drawbacks because they interfere with the mixing pattern (10).

6. Internally Illuminated photobioreactors

Impellers are included in the photobioreactor to stir the algal cultures. The cultures receive air and CO2 through the spargers. It is also possible to modify this kind of photobioreactor so that it can work with both natural and artificial light sources. In that instance, anytime the solar light intensity falls below a certain value (during cloudy weather or at night), the artificial light source is turned on (11).

Emphasis on AFC use for bioelectricity production using wastewater as feed source

Algae, a cheap source of oxygen, is used in SMCC to replace the external aeration system, which lowers running costs and improves performance. In a prior work on SMCC, it was found that maximum power densities of 38 mW/m2 and 16 mW/m2 for electrodes made of graphite felt-multi-walled carbon nanotubes (GF-MWNT). However, the use of a rotating cathode to increase oxygen availability produced a greater power density of 49 mW/m2. Although nitrogen-contaminated water that is released into water bodies can seriously impact eutrophication, the quality of the water, etc. Such contaminated water can be effectively used to grow algae. Removing nitrogen from the aquaculture pond, which can be found in both organic and inorganic forms as ammonium nitrogen (NH4 -N), nitrite nitrogen (NO2 -N), and nitrate nitrogen (NO3 -N), is a crucial process. Algae have the capacity to absorb nitrogen in both organic and inorganic forms, such as urea. The advantage of using pond sediments rather as culture media for algal development in a pond system has been made clear by the role of sediment and its overlaying water as a source of nutrients, further making it less expensive than a photo-bioreactor (22).

4. Conclusion

- Decision tree (DT) machine learning algorithms were applied for constructed microalgal dataset and showed significant classification for microalgal biomass concentration in relation to target microalgal parameters.
- Microalgal biomass concentrations were recorded at highest values when microalgae were *Monoraphidium* and *Nannochloropsis*. N and light levels were also contributing factors to biomass concentration.
- Bio-oil was at its highest values when pH at was high at ≥7.1 and microalgae were *Chlorella*, *Desmodesmus*, and *Monoraphidium*. Also, light, K, and biomass concentration were contributing factors for enhancing bio-oil content.
- Microalgal samples of *Chlamydomonas*, *Desmodesmus*, *Monoraphidium and Scenedesmus* required average light intensity levels to achieve their highest bio-oil content.
- Temperature at 27 °C was efficient for *Chlorella, Ettlia*, *Monoraphidium and Nannochloropsis* samples to achieve high biomass concentrations.
- pH levels were recorded optimal when microalgal bio-oil content was at highest levels ≥21 %w/w.

5. References

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