Hybrid rater to quantify and measure the severity of infection and spread of infection in muskmelon

Deeba Kannan[1], Amutha Balakrishnan[1], K. Mekala Devi[2], Nagendra Singh[3], P. Angelin Kiruba[4], Ravindran Ramkumar[5], Dhandapani Karthikeyan[6]
[1]Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur, India
[2]Department of Electronics and Communication Engineering, S.A. Engineering College, Chennai, India
[3]Department of Electrical Engineering, Trinity College of Engineering and Technology, Karimnagar, India
[4]Department of Mathematics, St. Joseph's Institute of Technology, Chennai, India
[5]Department of Electrical and Electronics Engineering, Dhanalakshmi Srinivasan University, Tiruchirappalli, India
[6]Department of Electrical and Electronics Engineering, SRM Institute of Science and Technology, Kattankulathur, India

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ABSTRACT

Disease severity index (DIS) is a way of calculating the percentage of infection spread across the field. The percentage of infection in each leaf has been considered at a time stamp is being calculated and based on that disease, severity of disease spread is analyzed. With the advancement in machine learning and deep learning algorithms in the field of computer vision, identification and classification of diseases is effortless. Percentage of infection in a particular leaf, disease index (DI) is calculated using image processing techniques like Otsu threshold method. With this DI and scales, grading the severity of the infection across the field can be achieved. In this paper various scales used for grading severity of infection namely Horsfall-Barratt (H-B scale) quantitative ordinal scale, Amended 20% ordinal scale, and nearest percent estimates (NPEs) in muskmelon is explored, and based on the empirical results Amended 20% ordinal scale is most efficient method of estimating the DIS is to use the midpoint of the severity scope for each class with twenty percent adjusted to ordinal scale. The results show that the density of leaves is directly proportional to spread of diseases in muskmelon plant.

Corresponding Author:

Dhandapani Karthikeyan
Department of Electrical and Electronics Engineering, SRM Institute of Science and Technology
Kattankulathur, India
Email: karthipncl@gmail.com

1. INTRODUCTION

The development and implementation of a hybrid rater for quantifying infection severity and tracking the spread of infections in muskmelon cultivation represent a significant advancement in precision agriculture. By combining imaging technology and machine learning, this tool empowers farmers to make data-driven decisions that can protect their crops, increase yield, and ultimately contribute to the sustainable production of high-quality muskmelons. The hybrid rater is a cutting-edge tool that combines advanced imaging technology, machine learning algorithms, and traditional disease assessment scales to provide accurate and real-time data on infection severity and spread in muskmelons.

Machine learning algotirhms are applied on the collected images that can identify and classify common muskmelon infections based on visual cues. These algorithms can distinguish between different types of pathogens, enabling precise diagnosis. By analyzing the images, the hybrid rater quantifies the severity of infection on each plant. It assigns a numerical score or a color-coded rating, indicating the extent of the disease's impact. This information helps farmers prioritize intervention strategies. The hybrid rater continuously monitors the muskmelon field over time, tracking the spread of infections. It can create heatmaps or visual representations of infection hotspots, allowing farmers to make informed decisions about disease management.

The disease severity index (DIS) is a single index number that is used to summarize lot of details about the disease severity. The DIS could be used to determine a cultivar's disease tolerance at a single area under a series of causes, assess the efficacy of pesticide, and to compare with other disease identification mechanisms. High-quality disease assessment data is necessary to make successful disease management recommendations, by adopting the standardized methodologies which can enhance the reliability and accuracy of severity estimations is critical. Bock *et al.* [1] used Horsfall-Barratt scale (H-B scale) combined with midpoint for estimating severity index in citrus plant disease. The scale is categorized with 12 classes based on the severity. This method seems to be better than direct estimation method with 10 class labels of each 10 equal intervals.

Bock *et al.* [2] used H-B scale for estimating severity index of pecan scab disease. The authors explored H-B scale and nearest point estimates (NPEs) for severity estimation and found HB scale to be most appropriate scale for estimating pecan scab disease. Jianqing *et al.* [3] compared three main scales namely HB, NPE and Amended 10% ordinal scale for estimating DIS calculation and found Amended 10% ordinal scale with midpoint estimates DIS better than other compared model. Sibiya and Sumbwanyambe [4], used fuzzy inference rules for estimating DIS of maize leaf disease. The author used ostu threshold method for calculating infected portion of leaf and a fuzzy based inference rule for estimating the severity in the leaf. The development and implementation of a hybrid rater for quantifying infection severity and tracking the spread of infections in muskmelon cultivation represent a significant advancement in precision agriculture. This work specifically applied in a single leaf image. Based on these work we considered three different scalar and two main intervals for estimating severity index of muskmelon leaf diseases.

2. PROPOSED METHODOLOGY

The objective of this chapter is to examine the process of calculating disease index (DI) using image processing techniques followed by estimating DIS using various scales. If disease evaluations are erroneous or unreliable, DIS might lead to wrong inferences over the data, which could lead to inappropriate disease management measures. The schematic representation of disease severity estimation module with hybrid rater algorithm is illustrated in Figure 1.

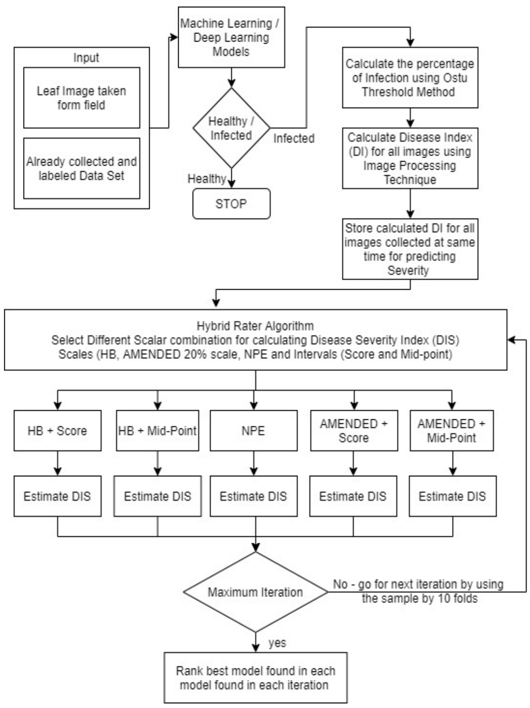

Figure 1. Flow of hybrid rater for DIS estimation

The steps involved to estimate the DIS are as follows:
- Calculate the percentage of infection using otsu threshold method [3]
- Calculate DI for all images using image processing techniques
- Store the DI for all Images collected simultaneously for predicting severity
- Select different scalar combinations for calculating DIS and scales - (HB, Vieira, Amended) and intervals (midpoint and score)
- Estimate the DIS
- If there is a deviation predicted from the actual severity, then proceed with different scalar combinations.
- Check for the maximum iterations with 10 folds of sample data, if not proceed with different scalar combinations.

Rank the best models found in each iteration indicating minute disease occurrences accurately and display the best model.

2.1. Percentage of infection using Otsu threshold method

First step in analysing the percentage of infection is to identify the infected portion in the leaf image. Otsu threshold method [3], [4] is used for identifying the infected portion from unhealthy leaves based on the colour feature. Otsu threshold method extracts different grey level intensities of the image which helps to separate the background from the foreground of the leaf image. By comparing the white pixels the number of infected area with the total pixels of leaf area from the segmented image, the severity index in the leaf area is calculated in expression (1):

$$DI = (PI/TP) \times 100 \tag{1}$$

where DI denotes disease index, PI denotes total infected pixel, and TP denotes total pixel of leaf area.

2.2. Disease severity index calculation

There are three types of scales [1], [2] normally in use for scaling DIS estimation based on the periodic range depending on the percentage of the leaf area with symptoms. They are, i) H–B scale quantitative ordinal scale, ii) Amended 20% ordinal scale, and iii) nearest percent estimates. Tables 1 to 3 shows the value ranges in H-B scale, Amended 10% ordinal scale, and NPE scales. Score is used to calculate the DIS for ordinal scale results. In (2) for a DIS [1] can be written as follows when class ranking is expressed in arbitrary scores.

$$DSI\ (\%) = \frac{[sum\ (class\ frequency \times score\ of\ rating\ class)]}{[(total\ number\ of\ plants) \times (maximal\ disease\ index)]} \times 100 \tag{2}$$

Table 1. H-B scale quantitative ordinal scale

Interval	Score	Midpoint
0%	0	0
0^+ –10%	1	5
10^+ –25%	2	17.5
25^+ –50%	3	37.5
50^+% disease	4	75

Table 2. Amended 20% ordinal scale

Interval	Score	Midpoint
0%	0	0
0^+–1%	1	0.5
1^+–4%	2	2.5
4^+–8%	3	6
8^+–12%	4	10
12^+–16%	5	14
16^+-20%	6	18
20^+-30%	7	25
30^+–40%	8	35
40^+–50%	9	45
50^+–70%	10	60
70^+% disease	11	85

Table 3. Nearest percent estimates scale

Interval	Score	Midpoint
0-1%	0	0.5
1+–2%	1	1.5
2+–4%	2	3
3+–5%	3	4
5+–7.5%	4	6.25
7.5+–10%	5	8.75
10+–15%	6	12.5
15+–20%	7	17.5
20+–30%	8	25
30+–40%	9	35
40+% disease	10	70

The denominator, comprises of maximal DI to scale the values in terms of percentage. The resultant values ranges from zero to hundred where zero represents no disease class and 100 represents seriously diseased class based on the level of severity near to death of the plant. Calculation without maximum DI, has been represented as in (3):

$$DIS = \sum \frac{(CF \times SRC)}{TO} \tag{3}$$

where 'CF' denotes class frequency, 'SRC' denotes score of rating class, 'TO' denotes total number of observations. The previous formula considers the maximum value of the interval. The midpoint values of the ranking intervals should be assumed to reduce the inherent bias. Otherwise, the DIS is often overlooked. When disease severity predictions are used as predictors of crop damage, the effects of overestimating disease severity can be significant [5]–[8]. Using the mid-point values the previous (3) can be modified into (4):

$$Modified\ DIS = MidQ + \sum \frac{CF * SRC}{TO} \times (MidQ + 1 - MidQ) \tag{4}$$

Where MidQ is the midpoint value for each scale value, CF denotes class frequency, SRC denotes score of rating class, and TO denotes total number of observations.

In addition to the various interval measurement methods, DIS is determined on a percentage basis using the above equations with ordinal scale data. The first scale used is the ordinal scale of H-B [5], [7] developed for pecan scab severity evaluation and an amended 10% ordinal scale (Amended) has been developed for a wider scale of plant disease measurement. HB scale consists of five intervals from (0%, 0+ -10%, 10+ - 25%, 25+ - 50% and 50% and above will be considered as diseased. Amended scale ranges from 0 to 11 totally 12 intervals as represented, (0% score 0, 0+ to 1 % score 1, 1+ to 4% score 2, 4+ to 8% score 3, 8+ to 12% score 4, 12+ to 16% with score 5, 16+ to 20% with score 6, 20+ to 30% with score 7, 30+ to 40% with score 8, 40+ to 50% with score 9, 50+ to 70% with score 10, and all above 70+% is considered a diseased category with score 11).

For uneven intervals, the mean severity estimate based on the grade of the interval (SCORE) is always lower than the mean severity estimate based on the midpoint value of the interval (MIDPOINT), according to our research. As an illustration: When estimating severity on two consecutive specimens (e.g. scores of 1 and 2), the DIS estimates using HB-S and HB-M are identical, as the DIS estimates using AM-S and AM-M.

For instance, using the SCORE method and the categories provided in Table 1:

$$(1 + 2)/2 = 1.5$$

then converted to:

$$DIS = (5\% + 17.5\%)/2 = 11.25$$

Using MIDPOINT method when the same category is considered in Table 1:

$$DIS = (5\% + 17.5\%)/2 = 11.25$$

same as that of H-B scale with score method even though the belongs to different score as 2 and 3.

In comparison to those computed using HB-M (or AM-M), the DIS estimate based on HB-S (or AM-S) is lower. Thus, using score method:

$$(1 + 3)/2 = 2.0$$

which is subsequently converted to the DIS estimate of 17.5%. For the MIDPOINT method:

$$(5 + 37.5)/2 = 21.25$$

In addition, the variability of the sample specimen values has a significant impact on estimations of mean severity, which are based on either the exponential midpoint transformation or the linear grade data. Furthermore, the accuracy of severity estimations using scales with equal intervals to generate the DIS is not higher than that of the amended 10% ordinal scale, when using unbiased estimates [9], [10].

To conclude, among the three scales HB scale has been considered as common ordinal scale where 50% and above will be treated as diseased category and with less intervals. This scale is not so accurate since it will miss all micro level details. Similar results occurs with NPE scale, where the interval between the scale increases in the rage of 5%, hence 40% and above is treated as diseased category, whereas Amended with 20% interval suits better to represent the micro level disease spread information. For our research work, the DIS has been calculated using Amended scale with 10% interval unit and using midpoint variation for calculation, so as not to miss the micro level values identified in the leaf images as shown in Table 4.

Table 4. Amended 20% ordinal scale with disease severity estimation

Interval	Score	Midpoint	Disease severity
0%	0	0	No disease
0^+–1%	1	0.5	Mild trace
1^+–4%	2	2.5	Mild
4^+–8%	3	6	Visible trace
8^+–12%	4	10	Light
12^+–16%	5	14	Moderate
16^+-20%	6	18	Visible lesion shape
20^+-30%	7	25	Lesion up to 10–15 mm
30^+–40%	8	35	High
40^+–50%	9	45	Severe disease
50^+–70%	10	60	Lesion up to 30–50 mm
70^+% disease	11	85	Large lesion

2.3. Growth chart for muskmelon

The plant species contemplated is muskmelon. Muskmelon is a kind of netted-rind melons from the Cucurbitaceae family, known for its musky-scented delicious juicy orange flesh. Muskmelon grows best on sandy or sandy loam soil with a pH of 6 to 6, enough fertility, and good drainage [11]–[13].

The maximum growth duration for muskmelon is 65 days. Initial 7 to 10 days are studied for its germination and first two leaf growth start at this stage. After 10 to 15 days, the plant will be transferred to the field. Hence the growth stage of the plant is calculated from the 10th day from seeding. 10th to 20th day is considered as stage 1 for growth where the plant gets adapted to the field environment and starts to grow up to one inch. Stage 2 is considered from 20th to 30th days, when the plant starts to grow and spread. Initial flowering begins at this stage of the growth.

At stage 3, the leaf cluster begins to develop and the plant begins to spread more closely to the next plant and, the growth is considered to be at stage 3 from the 30th to the 40th day. Development in the 40th to 50th days is considered as stage 4. The plant is fully grown at this period and little fruits emerge from the flowers. This is one of the significant phases in which fruit from flowers begins to develop. The spread of the disease is greater and the yield is heavily affected. From 50th to 60th day, the growth falls in stage 5.

At this stage, the growth of the plant will be stopped and fruits begin to mature. The disease spread at this stage is considerably high since the plants are closely clustered and spread across the region. The sixth stage contemplated between 60th and 65th day, when the fruit begins to ripen, and which is the last stage of development [14]–[16]. Figure 2 indicate the various stages of growth of muskmelon.

Figure 2 gives the various stages of growth of muskmelon. As per the data gathered from the agricultural field in real time, the growth map is drawn. The growth of the plant is measured in terms of centimeters, and is measured at an interval of 5 days. The longest branch of the plant is considered in our research. The final calculation is done as per the average of a few measurements observed from the field [17]–[19].

Data is gathered in the year 2018 between the period April and May and June to August at regular intervals. Between June and August the growth of the plant is supplementary due to consummate climatic conditions. The plant growth happens to attain a peek after the 25th day, while the change in plant growth is considerably reduced after the 50th day. Tables 5 and 6 presents the data collected from the field [20]–[23]. Muskmelon's growth chart is exhibited in the Figure 3.

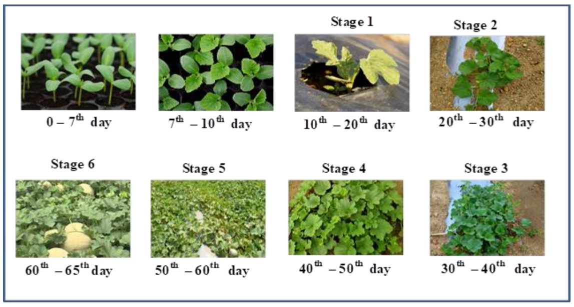

Figure 2. Growth stages for muskmelon

Table 5. Growth data gathered between April to May

Growth duration (2018)	Normalized temperature	Normalized humidity	Normalized soil moisture	Growth in CM	Change in growth	% change in growth
11-Apr	0.46	0.93	0.46	12.34	0	0
16-Apr	0.36	0.86	0.51	16.85	4.51	37
21-Apr	0.42	0.88	0.42	22.98	6.13	36
26-Apr	0.43	0.06	0.48	42.72	19.74	86
01-May	0.42	0.73	0.19	60.73	18.01	42
06-May	0.43	0.82	0.43	85.34	24.61	41
11-May	0.41	0.86	0.41	105.72	20.38	24
16-May	0.46	0.86	0.38	120.23	14.51	14
21-May	0.5	0.85	0.42	132.98	12.75	11
26-May	0.49	0.84	0.36	147.21	14.23	11
Avg	0.44	0.77	0.41	-	-	-
SD	0.04	0.25	0.09	-	-	-

Table 6. Growth data gathered between June to August

Growth duration (2018)	Normalized temperature	Normalized humidity	Normalized soil moisture	Growth in CM	Change in growth	% change in growth
27-Jun	0.3	0.97	0.24	14.23	0	0
02-Jul	0.38	0.88	0.56	21.71	7.48	53
07-Jun	0.31	0.82	0.61	32.47	10.76	50
12-Jun	0.36	0.84	0.53	57.12	24.65	76
17-Jun	0.36	0.82	0.59	72.35	15.23	27
22-Jun	0.36	0.7	0.28	93.87	21.52	30
27-Jun	0.36	0.78	0.53	113.73	19.86	21
01-Aug	0.36	0.82	0.56	134.45	24.72	22
06-Aug	0.39	0.84	0.61	145.32	3.87	3
11-Aug	0.42	0.88	0.65	154.76	12.44	9
Avg	0.36	0.84	0.52	-	-	-
SD	0.03	0.07	0.14	-	-	-

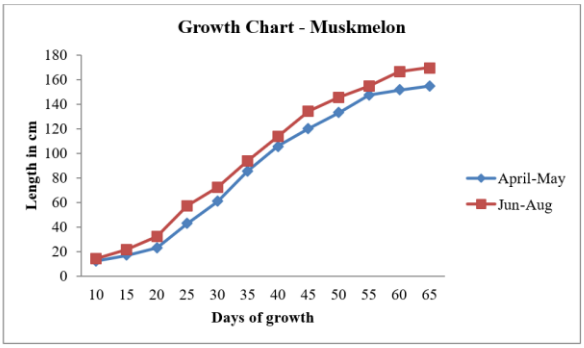

Figure 3. Growth chart for muskmelon (2018 data)

2.4. Likelihood of severity of spread based on growth stages

Spread of disease is directly proportional to DIS and its growth stage. As per the Figure 3, it is observed that the growth of plant increases after stage 3 and has consistent growth until stage 6. When the plant is clustered more, the spread of the infection will be more. Severity of spread increases as the plant growth increases [24], [25]. Maximum density of leaf is relatively equivalent to increase in spread of disease. Hence the spread of disease is estimated using (5):

$$Disease\ Spread\ (DS) = DSI \times \frac{Growth\ stage}{6} \tag{5}$$

The comparative analysis of the DIS and spread of disease is presented in Table 7. Thus, it concludes that when the densities of leaves are lesser, that is growth stage 1 to 3 and if DIS is less than 50%, then the disease spread is predicted to be less than 25%. Similarly, when the densities of leaves are greater, from growth stage 4 to 6 and if DIS is greater than 50%, then the disease spread are predicted to be more than 33%. It shows that density of leaves is directly proportional to spread of diseases in muskmelon plant.

Table 7. Pictorial representation of spread of disease based on DIS

DIS (%)	GS1 (%)	GS2 (%)	GS3 (%)	GS4 (%)	GS5 (%)	GS6 (%)
less than 10	<1.66	<3.33	<5	<6.66	<8.33	<10
10-25	1.6-4.1	0.3-8.2	5-12.5	6.6-16.5	8.3-20.8	10-25
25-50	4.1-8.3	8.2-16.5	12.5-25	16.5-33	20.8-41.6	25-50
50-75	8.3-12.4	16.5-24.7	25-37.5	33-49.5	41.6-62.5	50-75
75 and above	12.4-16.6	24.7-33	35.5-50	49.5-66	62.5-83.3	75-100

3. CONCLUSION

Percentage of infection in the leaf is calculated using Ostu threshold method. With that DI was calculate. To estimate DIS, three main scales were used namely, H-B scale quantitative ordinal scale, Amended 20% ordinal scale, and NPE. The most efficient method of estimating the DIS is to use the midpoint of the severity scope for each class with 20% adjusted to ordinal scale based on a normal scale of 20% prominence the severity of around 50% of infection, with low severity levels. This scale is widely used in plants for all forms of pantothenic attacks and involves the possibility of disease transmission depending on growth level. Experimental results shows that the density of leaves are directly proportional to spread of diseases in muskmelon plant. The growth pathogens can be simulated or suppressed when the appropriate environmental conditions are present.

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BIOGRAPHIES OF AUTHORS

Deeba Kannan is Assistant Professor at SRM Institute of Science and Technology, Chennai, Tamilnadu, India. She received her Ph.D. degree in Computer Science and Engineering, Chennai, Tamilnadu, India in 2021. Her research area is in IoT, deep learning, and machine learning. She has 20 internatinal journal publication and also published two patents. She can be contacted at email: karthikd@srmist.edu.in.

Amutha Balakrishnan is Professor, Department of Computer Science and Engineering, Chennai, Tamilnadu, India. She received her Ph.D. degree in Computer Science and Engineering, Chennai, Tamilnadu, India in 2012. Her main research area wireless networks, SDN, and machine learning. She had more than 60 international journals and published five patents. She can be contacted at email: amuthab@srmist.edu.in.

Ms. K. Mekala Devi is presently employed as an Assistant Professor in the Department of Electronics and Communication Engineering at S.A. Engineering College, Chennai. She attained her M.E degree from St. Peter's University in 2011, Chennai, and her BE degree from Vickram College of Engineering in 2005, Madurai. With 13 years of teaching experience, her primary areas of expertise encompass applied electronics, image processing, and machine learning. She can be contacted at email: mekaladevi@saec.ac.in.

Dr. Nagendra Singh is working as the principal of Trinity College of Engineering and Technology, Karimnagar, Telangana, India. He has worked in various positions, like HOD, Dean of Academics, and Exam Superintendent. He has published many research articles in reputed refereed SCI and Scopus-indexed journals and conferences. He has published eight book chapters and edited four books published by Indian and international publishers. He has been granted 14 design patents. He has organised many national and international conferences as well as faculty development programmes and seminars. His areas of interest are optimization techniques, AI, power systems, renewable energy systems, power electronics, smart antennas, and block chain technology. He is a life member of various professional bodies. He is a reviewer for many international journals. He can be contacted at email: nsingh007@rediffmail.com.

Mrs. P. Angelin Kiruba working as an Assistant Professor in the Department of Mathematics at St. Joseph's Institute of Technology, Chennai. She received her B.Sc., M.Sc., M.Phil. degree from University of Madras. She is pursuing her Ph.D. in Mathematics. She started her carrier as a Lecturer in Dr.M.G.R University from 2008 onwards. After four years she joined as an Assistant Professor in St. Joseph's Institute of Technology. She is having about 14 years of teaching experience till date. She can be contacted at email: angelinphd@gmail.com.

Dr. Ravindran Ramkumar is currently working as an assistant professor in the Department of Electrical and Electronics Engineering at Dhanalakshmi Srinivasan University, Trichy. He obtained his Ph. D under Faculty of Electrical Engineering from Anna University (2022), Chennai. He completed his M.E in Sethu Institute of Technology (2012), Madurai. He completed his BE in K.L.N. College of Information Technology (2008), Madurai. He has published more than 30 Scopus indexed journals and 6 SCI journals in his field. He has 11 years of teaching experience and 1-year industrial experience. His area of interest is power electronic converters, renewable energy, and micro grid. He can be contacted at email: 2019ramkr@gmail.com.

Dhandapani Karthikeyan received a B.E. degree in Electrical and Electronics Engineering from A.I.H.T College in Chennai, India (associated with Anna University in Chennai, India) in 2009, and an M.Tech. He received his bachelor's degree in Power Electronics and Drives from SRMIST (previously SRM University) in Kattankulathur, India, in 2013, and his Ph.D. in Multilevel Inverters in 2019. He is presently an Assistant Professor in the Department of Electrical Engineering at SRMIST (previously SRM University) in Kattankulathur and Chennai, India. His current research interests include power electronic, multilayer inverters, alternating current drives, and direct current drives. He is a member of several professional organizations, including the IEEE, IET, IEI, and ISCA. He can be contacted at email: karthipncl@gmail.com.