Hindawi
Journal of Food Quality
Volume 2022, Article ID 9282733, 16 pages
https://doi.org/10.1155/2022/9282733

Research Article

Understanding Gene Action, Combining Ability, and Heterosis to Identify Superior Aromatic Rice Hybrids Using Artificial Neural Network

Albin Sunny,[1] **Nihar Ranjan Chakraborty**,[1] **Anil Kumar**,[2] **Bhupesh Kumar Singh**,[3] **Amitava Paul**,[1] **Shalma Maman**,[4] **Anasooya Sebastian**,[5] **and Daniel Amoako Darko**[6]

[1]*Department of Genetics and Plant Breeding, Institute of Agriculture, Visva-Bharati University, Sriniketan 731236, West Bengal, India*
[2]*Department of Botany, Deen Dayal Upadhyaya Gorakhpur University, Gorakhpur, Uttar Pradesh, India*
[3]*B. S. Anangpuria Educational Institute, Alampur, Faridabad 121004, Delhi-NCR, India*
[4]*Indian Agricultural Research Institute, New Delhi, India*
[5]*Kerala Agricultural University, Thrissur, Kerala, India*
[6]*Institute for Environment and Sanitation Studies, University of Ghana, Accra, Ghana*

Correspondence should be addressed to Nihar Ranjan Chakraborty; nrchakraborty@gmail.com and Daniel Amoako Darko; dadarko@ug.edu.gh

Received 27 May 2022; Revised 12 June 2022; Accepted 22 June 2022; Published 31 July 2022

Academic Editor: Rijwan Khan

The aromatic rice represents a smaller but independent rice collection, the quality of which is considered to be highly acceptable. Farmers are interested in growing aromatic rice due to high premium market price. The prime objective of this study was to enhance genetic improvement of aromatic rice. Combining ability analysis (GCA and SCA) and gene action are studied in a set of 7×7 half-diallel crosses. Twenty-one hybrids along with their seven parents were assessed in randomized complete block design. Different quantitative characters were used to estimate the magnitude of heterosis. GCA and SCA significance for all traits revealed the importance of both additive and nonadditive genetic components. Several genes determine quantitative traits, with each gene having very little impacts and being easily influenced by environmental factors. Pusa Basmati-1 and Govindobhog were the best combiners among the seven parents. In terms of per se performance, heterosis, and SCA effects on seed yield per plant and important yield qualities, the crosses BM-24 Deharadun Pahari, Baskota × Tulaipanji, and Pusa Basmati-1 × Tulaipanji may be of interest. Because of its interconnected processing properties, ANN can play a critical role in this experiment. As a result, the current study was carried out to collect data and validate it using an artificial neural network (ANN) on the combining ability, gene action, and heterosis involved in the expression of diverse fragrant rice features. Using ANN, the validation of the result was done and it was found that the overall efficiency was approximately 99%.

1. Introduction

Aromatic rice varieties are a lesser but distinct collection of rice that have grown in popularity around the world. Aromatic rice is commonly known as Basmati rice in India, and it is typically grown in northwestern Indian states, such as Jammu and Kashmir, Haryana, Himachal Pradesh, Punjab, and parts of Uttar Pradesh [1]. In India, almost each state has its unique fragrant rice variety. Moreover, much has already been lost as a result of the green revolution, which prioritised production over quality [2]. Cultivation and production of aromatic rice are limited due to specific ecogeographic conditions and also are impeded by poor yield, late maturity, and lodging susceptibility. Furthermore, its agricultural adaption in eastern India is inadequate owing to the disintegration of its unique scent, grain quality, difficulties in milling due to extremely low head rice recovery, and high vulnerability to insects-pests [3]. According to research, the majority of aromatic rice genotypes are indigenous to the Indian subcontinent. Basmati farming has historically been restricted to the Himalayan foothills and a few places of the Indo-Gangetic Plain (IGP) [4–6]. Aromatic landraces and genotypes exhibit a wide range of genetic variation. Grain quality (both before and after cooking), scent, and flavour all consumer's decisions [7, 8]; therefore, increasing and genetically upgrading production is a primary priority. To design effective breeding methodology, knowledge about genotype genetic makeup is essential. Most agronomically essential features are driven by polygenes and are affected by environment to a higher extent, resulting in low heritability and making selection challenging. In complicated trait dissection and prediction, accounting for environmental variation has long been a challenge. Finding trends in environmental indices and linking them to changes in underlying genetic factors have huge significance for understanding complex characteristics in plants and forecasting future climates [9]. Although empirical breeding approaches have produced significant results, new tools and resources must be implemented in order to achieve the paradigm shift made appropriate to add significance to feeding the world's rapidly growing population in the face of climate change, dwindling resources, and changing lifestyles [10]. The success of crop variety development is based on the correct parent selection in addition to the environment and magnitude of gene activity involved in quantitative trait expression. Such information is provided by combining ability studies in order to successfully outline the breeding plan. This method assists in identifying parents with high general combining (GCA) and parental combinations with high particular combining (PC) (SCA). Combining ability analysis can help you find parents with good trait combining ability in the desired direction for a wide range of attributes. Combining ability analysis can be used to assess the relative importance and amount of additive and nonadditive forms of gene activity in the production of features [11, 12]. Selecting parents only based on their phenotypic performance is not always a good idea . Hybridization is the greatest effective method for flouting the produce maximum and developing high-yielding varieties. The success of any hybridization breeding programme is determined by the parents chosen. As a result, it is critical that parents be chosen based on their hereditary worth [13]. This technique for estimating additive and nonadditive gene action may be beneficial in determining the possibility of commercialising heterosis and isolating pure lines among the progenies of good hybrids. Increasing agricultural production in an environmentally sustainable way is heavily reliant on technological advancements and innovation research [14, 15]. This role is referred to as the "Digital Agricultural Revolution" by the United Nations Food and Agriculture Organization (FAO) [16]. Presently, the environment computer deals with a variety of services and allows users to address issues such as regulation, control, and orders. At this point, research in this field begins, including the modelling of an intelligent controller using fuzzy logic [17]. As a consequence, the present research used an artificial neural network to gather information on the inextricable connection, gene activity, and heterosis involved in the development of diverse fragrant rice traits.

The bulk of fragrant rice genotypes are indigenous to the Indian subcontinent, according to the study. Historically, Basmati growing was limited to the Himalayan foothills. Aromatic landraces and genotypes have a vast genetic variability. Most of the agronomically important traits are governed by by environment, resulting in low heritability and making selection difficult. In order to describe the breeding plan, such information is offered by merging ability studies. As a result, the current study employed an artificial neural network to collect data on the inextricable link, gene activity, and heterosis involved in the development of several fragrant rice features.

2. Materials and Methods

Two improved Basmati rice populations (Pusa Basmati-1 and BM-24) and five traditional cultivars of non-Basmati aromatic rice (Baskota, Govindobhog, Dehradunpahari, Gopalbhog, and Tulaipanji) (Table 1) were chosen as parents considering performance per se, grain type, panicle traits, phenotypic differences, and complementary characteristics.

2.1. Field Techniques. During the Kharif season of 2018, crosses were conducted utilising a 7×7 half-diallel mating strategy to produce 21 F_1 families. To synchronise flowering, parents were planted at 5-day intervals. For emasculation, the clipping process was used. Panicle which emerged 50–60% or halfway from the flag leaf was chosen for crossing. Leaf sheath from the panicle was removed. Care was taken not to break the culm. Spikelets from upper and lower portion of the panicle were removed and the remaining spikelets likely to open in the following day were chosen for emasculation. Pollination took place between 10:00 a.m. and 12:00 p.m. Panicle flowers were picked 25 to 30 days after pollination and stored separately with suitable documentation.

The twenty-one hybrids (Table 2) and their seven parents were evaluated in RCBD (randomized complete block design), with three replications, during the Kharif season 2019 at the Agricultural Farm, Institute of Agriculture, Visva-Bharati, Sriniketan, which is located at 23°19'N latitude and 87°42′E longitude and at an altitude of 58.9 m above sea level. Twenty-five-day-old seedlings were transplanted as one plant per hill, with a 25 25 cm gap between rows and plants. The crop was grown using the specified agronomic procedures. To evaluate genotypes and F1s based on the ten characters, observations are made on five plants chosen from the middle of each row in each replication.

2.2. Statistical Methods. In computing the ANOVA for combining ability effects, parents and crosses were treated as fixed variables, whereas replication was treated as a random

Table 1: List of parents used for crossing programme.

Parent no.	Parents	Important character	Source
1	Baskota	Medium slender grain, long awn, erect broad leaves, no lodging, sturdy stem, medium tall, and light green leaves	Government training centre (W.B.)
2	Pusa Basmati-1	Long awn, medium slender grain, broad erect leaf, no lodging, sturdy stem, medium tall, and dark green leaves	Rice sub-research station, Chakada (B.C.K.V, Mohanpur, Nadia, West Bengal)
3	BM-24	Medium tall, erect leaf, medium slender grain with short awn, light green leaf, lodging susceptible, and medium broad leaf	Rice sub-research station, Chakada (B. C. K. V., Mohanpur, Nadia, West Bengal)
4	Govindobhog	Short grain, medium broad leaf, medium tall, sturdy stem, light green leaf, no awn, pleasant aroma, and lodging susceptible, used as offerings to god and goddess, used for payas making.	South Bengal, Assam, Western and North-eastern part of India
5	Dehradun Pahari	Bold grain, brown husk, broad erect leaf, sturdy stem, dark green leaves, and no awn.	Government Training Centre, Phulia (W. B.)
6	Gopalbhog	Medium tall, broad erect leaf, no awn, medium bold grain, brown husk, and lodging susceptible	South Bengal, Assam, Western and North-eastern part of India
7	Tulaipanji	Narrow leaf, long awn, medium slender grain, medium tall, light green leaves, lodging susceptible, pleasant aroma, and traditional race of West Bengal	Uttar and Dakshin Dinajpur, Malda (W.B.)/ Deptt. Of Genetics & Plant and Crop Physiology (Visva-Bharati)

Table 2: List of crosses involving seven parents.

Cross no.	Pedigree of the crosses
1	Baskota × Pusa Basmati-1
2	Baskota × BM-24
3	Baskota × Govindobhog
4	Baskota × Dehradun Pahari
5	Baskota × Gopalbhog
6	Baskota × Tulaipanji
7	Pusa Basmati-1 × BM-24
8	Pusa Basmati-1 × Govindobhog
9	Pusa Basmati-1 × Dehradun Pahari
10	Pusa Basmati-1 × Gopalbhog
11	Pusa Basmati-1 × Tulaipanji
12	BM-24 × Govindobhog
13	BM-24 × Dehradun Pahari
14	BM-24 × Gopalbhog
15	BM-24 × Tulaipanji
16	Govindobhog × Dehradun Pahari
17	Govindobhog × Gopalbhog
18	Govindobhog × Tulai Panji
19	Dehradun Pahari × Gopalbhog
20	Dehradun Pahari × Tulaipanji
21	Gopalbhog × Tulaipanji

effect. The GCA and SCA effects were estimated using Griffing's [18] diallel technique 2, model 1.

The statistical model is as follows:

$$Y_{ij} = \mu + g_i + g_j + s_{ij} + \frac{1}{bc} \cdot \sum \sum eijkl, \tag{1}$$

where $k = 1$, $i = 1, \ldots, p$, $j = 1, \ldots, p$, b = number of blocks, c = number of plants. $Y_{ij\,=}$ mean of the $i \times j^{\text{th}}$ genotype, μ = general mean, $g_{i\,=}$ general combining ability effect of the i^{th} parent, $g_{j\,=}$ general combining ability effect of the j^{th} parent, $s_{ij\,=}$ specific combining ability effect of the $i \times j^{\text{th}}$ cross combination, $e_{ijk\,=}$ mean error effect, i = male parent involved in $i \times j$ cross combination, j = female parent involved in $i \times j$ cross combination, p = number of parental lines, and r = number of replications.

The restrictions imposed for this model are $\sum g_i = 0$ and, $(\sum s_{ij} + s_{ii}) = 0$ (for each i), where i = number of parents.

The orthogonal partitioning of the genotype sum of squares into its combining ability components, as well as the mean square expectations, is shown as follows:

$$\text{sum of squares due to GCA (SSg)} = \frac{1}{(p+2)} \cdot \left[\sum (Y_i + Y_{ii})^2 - \frac{4}{nY^2} \right], \tag{2}$$

$$\text{sum of squares due to SCA (SSs)} = \sum \sum Y_{ij}^2 - \frac{1}{(p+2)} \cdot \left[\sum \left(Y_j + Y_{jj}\right)^2 \right] + \frac{2}{(p+1)(p+2)} Y. \tag{3}$$

2.3. Artificial Neural Network (ANN) Validation. ANN has gained in popularity and now plays a key part in technological advancement. With the growth of industrial automation and the Internet of Things, it is now simpler than ever to gather data and monitor food dryness, extrusion, and sterilization [19, 20]. Throughout the industrial revolution, ANN has proven to be useful in food processing operations such as food classification, safety, and quality control. Shallow learning techniques (i.e., the use of already generated ANNs) in food processing have gained increasing attention in recent years, since researchers have demonstrated that they can tackle a variety of complex real-world problems [21, 22]. Food producers are increasingly employing artificial neural networks in all aspects of agricultural production and farm management. Artificial intelligence approaches help agricultural decision-making systems, optimise storage and transportation processes, and estimate expenditures based on management direction. Incorporating machine learning approaches into a farm's "life cycle" demands the ability to manage massive amounts of data created throughout the growing season, as well as the requisite software. More and more farms are turning to artificial intelligence-based tools as precision farming and digital agriculture become more prominent. The architecture of ANN is shown in Figure 1 and as stated below.

In order to learn and make conclusions, the model receives inputs/information from the outside world via the input layer. The data from the input nodes is directed to the hidden layer, which follows. The hidden layer is made up of a network of neurons that process all of the input data. There can be any number of hidden layers in a neural network. The most fundamental network contains only one hidden layer. The output layer's computations are utilised to derive the model's output/conclusions. The output layer may contain one or more nodes.

With the advancement of industrial automation and the Internet of Things, gathering data and monitoring food dryness, extrusion, and sterilization is now easier than ever. Food categorization, safety, and quality control have all been demonstrated to benefit from ANN techniques for shallow learning. Agricultural decision-making systems benefit from artificial intelligence technologies, which optimise storage and transportation operations and anticipate expenses depending on management direction. Incorporating machine learning methodologies into the "life cycle" of a farm necessitates the capacity to manage large volumes of data generated throughout the growing season, as well as the necessary tools. As precision farming and digital agriculture grow more popular, more farmers are turning to artificial intelligence-based systems.

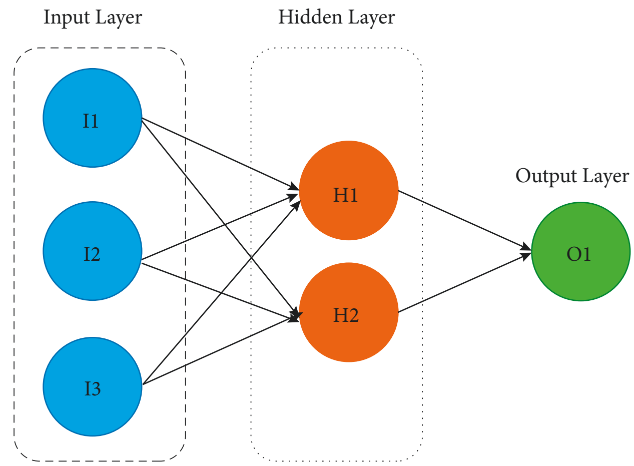

Figure 1: ANN architecture.

3. Results and Discussion

The analysis of variance explained substantial differences here between parents (P), F1, and the P vs. F1 interaction (Table 3). This revealed that the treatments had a lot of genetic variability amongst them. For almost all of the characteristics, significant differences due to the P vs. F_1 interaction revealed significant differences in SCA among hybrids. The findings highlighted the relevance of combining aptitude studies and suggested that selecting acceptable parents and crosses for the generation of appropriate varieties and hybrids had a decent chance.

3.1. Nature of Gene Action

3.1. Nature of Gene Action. Estimates of extremely significant GCA and SCA variance (Table 3) for all of the traits demonstrated the involvement of both additive and nonadditive genes in the manifestation of the characters. The inheritance of several quantitative aspects in rice, including additive and nonadditive gene effects, confirmed prior findings by Kargbo et al. [23], Fels et al. [24], and Mazal et al. [25]. The ratio of $\sigma 2$ GCA/$\sigma 2$ SCA was less than unity for all the characters that also indicated predominance of nonadditive genetic variance. The results were in accordance with the earlier findings of Mallikarjuna et al. [26] for culm length; and Mallikarjuna et al. [26] for panicle number plant−1, spikelet fertility and panicle length; Patil et al. [27] and for grain yield plant−1 Bano and Singh [28] grain yield plant^{-1} in rice. Therefore, heterosis breeding may be helpful for this trait. In contrast, spikelet fertility and seed yield/plant were controlled principally by additive gene action, and therefore, transgressive breeding is a superior option for these traits. Furthermore, other breeding methodologies such as biparental mating, reciprocal recurrent selection, or diallel selective mating [29] may be reconstituted than conventional pedigree method which would leave the unfixable components of genetic variances untapped for grain yield and its associated traits which were controlled mainly by additive along with nonadditive gene action.

3.2. GCA Effects and Performance Per Se of Parents. The information about the parents for hybridization comes from the combining ability analysis. Parental line phenotypic selection can be done based on GCA or parental line performance in general. The GCA is commonly attributed to genetic additive effects and fixable factors [30]. As a result, in plant breeding, selecting parents based on GCA impacts is critical.

The GCA effect and mean performance (Table 4) can both be used to evaluate parents for a breeding programme. In light of this, those parents who performed well in terms of both mean performance and GCA effect were considered good general combiners in the current study. According to

Table 3: Combined analysis of variance for diallel crosses and analysis of variance for combining ability for 10 quantitative traits in the F1 generation.

	df	Plant height	Main panicle length	Exsertion length	Leaf area	Total effective tillers	Spikelet number/panicle	Filled grains per panicle	Fertility (%)	Test weight 250 seeds	Seed yield per plant
Parents	6	906.98***	17.69***	29.55**	132.59***	19.45	12110.97***	5553.08***	428.08***	1.92**	273.14*
F1	20	484.28***	10.73***	29.27***	175.54***	59.41***	11301.01***	5558.83***	402.1***	1.9**	258.55**
P v F1	1	1294.15***	0.002	9.45	117.95*	11.08	31600.18***	1780.49*	1657.73***	1.56**	287.68
Replication	1	6.94	0.037	5.54	2.82	35.55	134.63	339.87	19.25	0.016	141.32
Error	27	40.36	1.02	5.81	20.27	12.99	381.51	250.51	7.16	0.030	97.61
GCA	6	290.54***	6.19***	10.44**	114.33***	20.78*	9072.78***	1804.75***	477.5***	1.18**	218.56**
SCA	21	307.98***	5.87***	15.40***	72.68***	25.4***	5271.74***	2967.11***	155.67***	0.879**	106.54*
Var GCA		30.04	0.631	0.837	11.58	1.59	986.89	186.61	52.66	0.129	18.86
Var SCA		287.8	5.35	12.5	62.54	18.9	5080.98	2841.86	152.1	0.864	57.74
Predictability factor		0.173	0.191	0.118	0.270	0.144	0.280	0.116	0.409	0.230	0.395

*, **, ***Significant at $p = 0.05$, 0.01, and 0.001, respectively. Var GCA: variance due to GCA and Var SCA: variance due to SCA.

Table 4: GCA effect and per se performance of parents in the F1 generation for 10 quantitative characteristics.

Parents	Plant height		Main panicle length		Exsertion		Leaf area		Total effective tillers		Spikelet number/panicle		Filled grains per panicle		Fertility (%)		Seed yield per plant		Test weight	
	Per se	GCA	Per se	GCA	Per se	GCA	Per se	GCA	Per se	GCA	Per se	GCA	Per se	GCA	Per se	GCA	Per se	GCA	Per se	GCA
Baskota	119.53	−3.37*	28.9	0.215	6.19	−0.260	28.68	−0.228	10.21	−2.19**	179.34	4.17	109.84	1.54	61.27	−2.02**	22.22	−0.152	5.62	0.529**
Pusa Basmati-1	178	11.67***	33.92	1.76***	11.34	1.24*	31.37	4.24***	11	0.709	297.83	43.77***	190	19.27***	63.8	−5.09***	29.79	9.26***	3.99	0.039
BM-24	149.38	−3.8*	24.75	−0.329	2.25	−0.191	28.04	−4.1***	11.75	1.35	191.5	39.4***	113.75	1.13	59.42	−11.04***	19.91	−1.65	5.66	−0.351**
Govindobhog	161.75	1.32	27.69	−0.039	5.69	−0.1	46.25	4.53***	13.88	−1.23	276.75	−4.2	221.75	3.06	79.68	−0.235	45.18	3.53	6.02	0.359**
Dehradun Pahari	125.2	−5.34***	31.2	−0.412	5.3	0.18	23.7	−4.3***	8.5	−0.653	104.23	−27.83***	74.2	−19.12***	71.22	1.19	10.14	−4.26	5.64	−0.069
Gopalbhog	130.8	0.603	27.05	−0.597*	4.8	−1.45*	39.95	1.02	14.3	2.18**	131.4	−38.66***	125.84	−17.71***	95.8	5.67***	27.49	−1.96	5.47	−0.010
Tulaipanji	154.6	−1.07	29.65	−0.596*	13.1	1.48**	26.05	−1.15	17.9	−0.175	109.4	−16.65***	99.54	11.83	91.12	11.53***	13.36	−4.44*	3.47	−0.495**

*, **, ***Significant at $p = 0.05$, 0.01, and 0.001, respectively.

Abd El-Aty et al. [31] and Rajan et al. [32], the average performance of the parents together with the nature of combining abilities gives the criteria for selecting parents for hybridization.

This characteristic may benefit from heterosis breeding. Transgressive breeding is a better choice for these variables since spikelet fertility and seed yield/plant were mostly controlled by additive gene activity. The combining ability analysis provides information about the parents for hybridization. GCA or parental line performance in general can be used to choose parental lines for phenotypic selection. In the current study, parents who did well in terms of both mean performance and GCA impact were regarded good general combiners. The criteria for selecting parents for hybridization are based on the average performance of the parents as well as the type of merging skills.

In the F_1 generation among the seven parents, Baskota had significant negative GCA effects and high performance per se for plant height, total effective tillers, and fertility percentage, whereas Pusa Basmati-1 had significant positive GCA effects and high performance per se for plant height, main panicle length, exsertion length, leaf area, total grains per panicle, filled grains per panicle, and seed yield per plant. Other cultivars also have either significant positive or negative GCA effects for different traits. The significant and positive GCA effects for grain yield plant^{-1} were exhibited by Pusa Basmati 1, and it also showed positive and significant GCA effects for other important traits, viz., as a result, simultaneous improvements in yield, yield characteristics, and other associated qualities are attainable and critical for increasing rice yield potential. Grain yield and most other yield component qualities have additive gene effects that can be fixed. Traditional breeding strategies, such as the combination of compatible donor with outstanding restorer parents in autogamous crops like rice, can still result in significant improvements in grain production and critical yield qualities in rice, leading to the development of high yielding varieties.

Due to the trait of complementation of characters, which is dominant among component characters, none of the parents had high general combining ability for all the characters based on GCA impacts. Therefore, to assess overall good general combiner for all the characters separately, individual parent was given a score for singly trait as per their GCA effect. A score "+1" was assigned for any significant GCA effects in desirable direction, while "−1" was assigned for any significant GCA effect in undesirable direction. A score of "0" was assigned for any nonsignificant GCA effect in any direction. After completing this process, Pusa Basmati-1 and, for the most part, Govindobhog have shown the finest overall general combiner (Table 5). More heterosis can be harnessed by using these parents in the hybridization programme. Pahari of Dehradun appeared to be a poor combiner.

3.3. SCA Effects and Performance Per Se of Crosses. SCA effects, which are hypothesized to be expressions of nonadditive components of genetic variation, are particularly valuable for judging the genetic merit of crosses as breeding material. They have been linked to the presence of linkage during the repulsion phase or the combination of positive favourable genes from separate parents [33].

Generally, the crosses showing significant and desirable SCA effects were accompanied by better performance per se for respective traits (Table 6), but sometimes this relationship did not show a beneficial direction. Thus, the development of superior hybrid crosses will be evaluated with performance per se along with SCA effects. Baskota × Tulaipanji had significant and positive SCA effects for grain yield plant^{-1} along with filled grain, spikelet number test weight, and panicle weight. In contrast, it showed negative and significant SCA effect for exsertion length. Among five good specific combining crosses (Table 7), Pusa Basmati-1 × BM-24 showed great performance per se and significant and positive SCA effect for leaf area. B.M-24 × Gopalbhog displayed great presentation per se and significant and positive SCA effect for total effective tiller. BM-24 × Dehradun Pahari had great presentation per se along with the positive SCA-effect for spikelet number panicle^{-1}, filled grain per panicle, and seed yield per plant. Baskota × Tulaipanji had high performance per se along with positive and significant SCA effect for seed yield per plant. Pusa Basmati-1 × Tulaipanji had high performance per se along with positive and significant SCA effect for test weight.

Hence, these crosses may be utilised for the exploitation of heterosis for yield and yield-related traits in rice. Therefore, the acceptable breeding strategy for attaining high yield would be the full or partial utilization of hybrid vigour by developing hybrid, synthetic, or composite cultivars. Several crossings had substantial and desirable SCA effects for one or more examined variables, but none emerged as a suitable specific combiner for all traits in F1 generations. In general, crossings with significant and desired SCA effects were related with superior performance for the corresponding characteristics, but this connection did not always show up in the F1 generations.

3.4. Heterosis. Generally, positive heterosis is preferred in the selection for yield and its components, whereas negative heterosis is impulsed for short plant height [34, 35] and panicle exertion.

Three crosses Pusa Basmati-1 × BM-24, Pusa Basmati-1 × Tulaipanji, and Govindobhog × Tulaipanji exhibited negative and significant midparent heterosis, while only one cross (Govindobhog × Tulaipanji) showed negative and significant heterosis over both mid- and better-parent for plant height. Mostly breeders are focused in short stature rice plants to bypass the lodging trouble. Therefore, negative heterosis is useful to avoid the tall plant height. Significant negative heterosis for culm length in rice has been reported by Devi et al. [36] and Gaballah et al. [37]. BM-24 × Gopalbhog (23.55%) and Dehradun pahari × Tulaipanji (19.13%) showed maximum midparent, respectively, for main panicle length. Less exsertion length are required for better plant type to skip lodging. Seven crosses including Baskota × Dehradun Pahari (70.27%) exhibited positive and

Table 5: Scoring of parents in respect of rank in GCA effects for quantitative characters (F1).

Parents	Plant height	Main panicle length	Exsertion length	Leaf area	Total effective tillers	Spikelet number/ panicle	Filled grains per panicle	Fertility (%)	Test weight	Seed yield per plant	Total	Category
Baskota	−1	0	0	0	−1	0	0	−1	1	0	−2	Low
Pusa Basmati-1	1	1	1	1	0	1	1	−1	0	1	6	High
BM-24	−1	0	0	−1	0	1	0	−1	−1	0	−3	Low
Govindobhog	0	0	0	1	0	0	0	0	1	0	2	High
Dehradun Pahari	−1	0	0	−1	0	−1	−1	0	0	0	−4	Low
Gopalbhog	0	−1	−1	0	1	−1	−1	1	0	0	−2	Low
Tulaipanji	0	−1	1	0	0	−1	0	1	−1	−1	−2	Low

Table 6: Performance of F_1 hybrids and SCA -effects for ten quantitative characters.

Crosses	Plant height		Main panicle length		Exsertion		Leaf area		Total effective tillers		Spikelet number/ panicle		Filled grains per panicle		Fertility (%)		Test weight		Seed yield per plant	
	Per se	SCA	Per se	SCA	Per se	SCA	Per se	SCA	Per se	SCA	Per se	SCA	Per se	SCA	Per se	SCA	Per se	SCA	Per se	SCA
Baskota × Pusa Basmati-1	168.25	6.02	29.44	−1.54*	6.83	−1.81	33.75	−4.78	15.50	3.71	282.75	9.32	191.85	27.72*	67.88	9.8***	6.30	0.895**	45.41	8.36
Baskota × BM-24	171.50	24.7***	30.00	1.10	12.13	4.91**	30.58	0.395	12.25	−0.188	328.00	58.94***	164.00	18.00	50.02	−2.11	3.79	−1.22**	27.91	1.77
Baskota × Govindobhog	137.90	−13.98**	30.54	1.35*	5.04	−1.36	38.82	−0.002	8.65	−1.21	161.25	−64.22***	86.45	−61.47***	53.61	−9.33***	5.38	−0.340**	27.06	−4.26
Baskota × Dehradun Pahari	148.75	3.53	28.38	−0.439	9.13	1.54	44.59	14.60***	7.00	−3.43	231.75	29.92*	163.25	37.50**	70.61	6.25**	5.49	0.192	19.29	−4.23
Baskota × Gopalbhog	166.50	15.33**	29.38	0.745	9.10	3.14	30.84	−4.47	10.54	−2.73	208.79	17.79	134.38	7.21	64.36	−4.48*	5.48	0.129	19.23	−6.60
Baskota × Tulaipanji	169.19	19.7***	28.50	−0.130	4.38	−4.51**	38.17	5.03	12.13	1.22	270.25	57.24***	200.88	44.18***	74.35	−0.348	5.75	0.884**	38.80	15.79*
Pusa Basmati-1 × BM-24	149.59	−12.21**	32.34	1.89**	5.86	−2.85	48.82	14.16***	12.84	−2.50	299.92	−8.74	159.63	−4.1	53.30	4.24*	4.83	0.30*	41.37	5.82
Pusa Basmati-1 × Govindobhog	164.38	−2.54	32.55	1.82**	7.75	−0.147	56.09	12.80***	12.25	−0.509	340.50	75.44***	219.50	53.86***	64.50	4.63*	6.25	1.02**	53.32	12.59
Pusa Basmati-1 × Dehradun Pahari	166.50	6.24	29.50	−0.857	10.33	1.247	32.18	−2.27	17.00	3.67	196.00	−45.43**	85.00	−58.47***	43.36	−17.92***	4.66	−0.143	33.20	0.266
Pusa Basmati-1 × Gopalbhog	184.50	18.3***	30.75	0.577	14.50	7.05***	39.10	−0.678	19.50	3.33	278.50	47.90***	152.50	7.62	54.89	−10.88***	3.85	−1.01**	40.06	4.82
Pusa Basmati-1 × Tulaipanji	147.25	−17.28***	25.50	−4.67***	4.50	−5.88***	41.63	4.02	13.50	−0.309	204.50	−48.11***	131.50	−42.92***	64.16	−7.46***	5.15	0.774**	33.89	1.46
BM-24 × Govindobhog	155.75	4.3	25.75	−2.89***	12.00	5.53**	27.75	−13.19***	5.00	−8.40**	184.00	−76.7***	98.25	−49.26***	53.34	−0.576	3.42	−1.43**	11.32	−18.50**
BM-24 × Dehradun Pahari	132.50	−12.29**	30.25	1.98**	8.25	0.598	20.48	−5.64	24.50	10.52***	341.00	103.94***	141.00	15.66	41.21	−14.13***	4.36	−0.053	47.46	25.43***
BM-24 × Gopalbhog	132.75	−17.98***	32.00	3.91***	7.00	0.974	23.93	−7.51*	28.50	11.69***	203.00	−23.23	71.00	−55.75***	35.05	−24.78***	4.21	−0.261*	21.51	−2.82
BM-24 × Tulaipanji	156.40	7.34	29.30	1.21	9.86	0.903	37.58	8.32**	11.80	−2.65	419.60	171.36***	295.40	139.11***	70.42	4.74*	3.58	−0.406**	19.29	−2.23
Govindobhog × Dehradun Pahari	162.44	12.53**	27.73	−0.831	5.62	−1.23	41.44	6.7*	13.13	1.73	231.21	37.74**	136.67	9.40	59.12	−7.03***	4.95	−0.173	24.92	−2.29
Govindobhog × Gopalbhog	176.25	20.4***	28.25	−0.126	1.25	−3.97*	36.63	−3.43	16.00	1.77	160.50	−22.14	91.50	−37.18**	57.05	−13.58***	4.33	−0.856**	23.96	−5.55
Govindobhog × Tulai Panji	123.10	−31.08***	31.55	3.17***	9.26	1.11	29.67	−8.23**	12.40	0.525	135.23	−69.42***	98.24	−59.98***	72.45	−4.04*	5.53	0.834**	24.36	−2.34
Dehradun Pahari × Gopalbhog	160.70	11.51**	24.90	−3.10***	2.69	−3.71*	29.80	−1.44	12.70	−2.10	140.86	−18.14	129.20	22.70*	91.72	19.67***	4.92	0.161	24.32	2.61
Dehradun Pahari × Tulaipanji	162.10	14.58**	25.23	−2.77***	16.32	6.99***	21.54	−7.53*	9.00	−3.45	204.20	23.18	171.00	34.96**	83.75	5.85**	2.41	−1.86**	15.67	−3.23
Gopalbhog × Tulaipanji	154.60	1.13	27.35	−0.469	4.15	−3.55*	45.12	10.73**	10.00	−5.28*	201.56	31.37*	157.00	19.55	77.90	−4.49*	4.86	0.533**	21.81	0.605

*, **, ***Significant at $p = 0.05$, 0.01, and 0.001, respectively.

Table 7: Some of the best F_1 hybrids in terms of high SCA effect and per se performance for different quantitative characters.

Character	Hybrids	SCA effect	Better parent heterosis	Per se performance
Plant height	Govindobhog × Tulaipanji	-31.08^{***}	-20.38^{**}	123.10
	BM-24 × Dehradun Pahari	-12.29^{**}	5.83	132.50
	BM-24 × Gopalbhog	-17.98^{***}	1.49	132.75
	Baskota × Govindobhog	-13.98^{**}	15.37^{**}	137.90
Main panicle length	BM-24 × Gopalbhog	3.91^{***}	18.30^{**}	32.00
Exsertion length	Baskota × BM-24	4.91^{**}	95.88^{*}	12.13
	BM-24 × Govindobhog	5.53^{**}	110.90^{*}	12.00
Leaf area	Baskota × Dehradun Pahari	14.60^{***}	55.50^{**}	44.59
	Pusa Basmati-1 × BM-24	14.16^{***}	55.64^{**}	48.82
	Pusa Basmati-1 × Govindobhog	12.80^{***}	21.26^{*}	56.09
	BM-24 × Tulaipanji	8.32^{**}	34.02^{*}	37.58
Total effective tillers	BM-24 × Dehradun Pahari	10.52^{***}	108.51^{**}	24.50
	BM-24 × Gopalbhog	11.69^{***}	99.30^{**}	28.50
Spikelet number/panicle	Baskota × BM-24	58.94^{***}	71.28^{**}	328.00
	Baskota × Tulaipanji	57.24^{***}	50.70^{**}	270.25
	Pusa Basmati-1 × Govindobhog	75.44^{***}	14.33^{*}	340.50
	BM-24 × Dehradun pahari	103.94^{***}	78.07^{**}	341.00
	BM-24 × Tulaipanji	171.36^{***}	119.11^{**}	419.60
Filled grain/panicle	Baskota × Dehradun pahari	37.50^{**}	48.63^{**}	163.25
	Baskota × Tulaipanji	44.18^{***}	82.89^{**}	200.88
	BM-24 × Tulaipanji	139.11^{***}	159.69^{**}	295.40
	Dehradun Pahari × Tulaipanji	34.96^{**}	71.80^{**}	171.00
	Dehradun Pahari × Tulaipanji	5.85^{**}	8.09^{*}	83.75
Test weight	Baskota × Pusa Basmati-1	0.895^{**}	12.01^{**}	6.30
	Pusa Basmati-1 × Tulaipanji	0.774^{**}	29.07^{**}	5.15
Seed yield/plant	BM-24 × Dehradun pahari	25.43^{***}	138.41^{**}	47.46
	Baskota × Tulaipanji	15.79^{*}	74.66	38.80

*, **, ***Significant at $p = 0.05$, 0.01, and 0.001, respectively.

significant midparent heterosis, while six crosses including Pusa Basmati-1 × BM-24 (55.64%) presented positive. Heterosis for grain yield is the product of the interaction of simultaneous increase in the expression of heterosis of its components which was suggested by Grafius [38]. In this experiment, five hybrids showing extremely noteworthy heterosis over midparent explained cumulative heterosis for principal yield attributes like days to flowering, panicle number plant-1, panicle length, secondary branches panicle-1, and spikelet number panicle-1.

3.5. Heterosis and Combining Ability Effects. Heterosis over midparent and SCA effects of crosses (Table 8) revealed that the majority of crosses showed significant heterosis over midparent, as well as positive and significant SCA effects in the desired direction, indicating the predominance of nonadditive gene action for the expression of observed average heterosis. Table 8 shows the heterosis over mid- and better-parent for ten quantitative characters in the F1 generation. A grouping of the parents was tendered as high GCA (significant GCA effect in the desired direction) and low GCA parents (nonsignificant and significant GCA effects in undesirable order). As per the above suggested grouping (Table 9), F_1 hybrids show useful significant midparent heterosis as per the GCA effects of the parents associated in the three distinct groups. Peng and Virmani [39], Casco et al. [40], and Anusha et al. [41] reported no relation to forecast that parents with high positive GCA effects would always merge to give rise to hybrids with high positive SCA effects. The current results are in corroboration to that of Mallikarjuna et al. [26], wherein they argued that superior SCA effects were produced by crosses involving all kinds of combinations, viz., High × High, High × Low, Low × High, and Low × Low general combiners. There were maximum numbers of hybrids with significant heterosis-associated Low × Low GCA parents (59.68%) followed by High × Low GCA parents (37.09%) and High × High GCA parents (3.23%). The crosses show significant specific combining ability (SCA) effect which committed high performance [27, 42]. The crosses which involved the parents with Low × Low GCA effects and the superior performance were because of nonadditive (dominance and epistasis) genetic effects [43]. The high yield potential of crosses possessing high SCA with High × Low combining parents is assigned to interaction between positive alleles from good combiners and negative alleles from poor combiners. BM-24 × Dehradun Pahari cross combination in the F_1 generation revealed high mean value for grain yield accompanying significant SCA effects for corresponding trait involving Low × Low general combiner parents. It would be possible to regain elite transgressive segregants in segregating generation. Sing et al. [44], Devi et al. [45], ElShamey et al. [46] indicated the crosses showing high SCA associating good general

Table 8: Heterosis over mid- and better-parent for ten quantitative characters in the F1 generation.

Crosses	Plant height		Main panicle length		Exsertion length		Leaf area		Total effective tillers		Spikelet number/ panicle		Filled grains per Panicle		Fertility (%)		Test weight		Seed yield per Plant	
	H (mp)	*H* (bp)	*H* (mp)	*H* (bp)	*H* (mp)	*H* (bp)	*H* (mp)	*H* (bp)	*H* (mp)	*H* (bp)	*H* (mp)	*H* (bp)	*H* (mp)	*H* (bp)	*H* (mp)	*H* (bp)	*H* (mp)	*H* (bp)	*H* (mp)	*H* (bp)
Baskota × Pusa Basmati-1	13.10**	40.77**	−4.27*	−13.21**	−22.11	−39.79	12.41	7.59	46.16	40.91	18.51*	−5.06	27.97**	0.97	8.54*	6.39	31.01**	12.01**	74.63*	52.44
Baskota × BM-24	27.56**	43.48**	11.84**	3.81	187.32**	95.88*	7.84	6.64	11.57	4.26	76.90**	71.28**	46.70**	44.18**	−17.11**	−18.35**	−32.80**	−33.04**	32.53	25.64
Baskota × Govindobhog	−1.95	15.37**	7.92*	5.66	−15.15	−18.58	3.61	−16.08	−28.17	−37.66	−29.29**	−41.73**	−47.86**	−61.01**	−23.97**	−32.72**	−7.56**	−10.63**	−19.71	−40.11
Baskota × Dehradun Pahari	21.57**	24.45**	−5.57	−9.05**	58.83	47.42	70.27	55.50**	−25.17	−31.44	63.45**	29.23*	77.41**	48.63**	6.60	−0.85	−2.53	−2.66	19.26	−13.17
Baskota × Gopalbhog	33.03**	39.30**	5.00	1.64	65.61	47.01	−10.12	−22.80	−13.99	−26.29	34.38**	16.42	14.04	6.79	−18.04**	−32.81**	−1.13	−2.49	−22.64	−30.07
Baskota × Tulaipanji	23.44**	41.55**	−2.65	−3.88	−54.64*	−66.60**	39.49	33.10*	−13.73	−32.26	87.20**	50.70**	91.89**	82.89**	−2.42	−18.40**	26.58**	2.31	118.13*	74.66
Pusa Basmati-1 × BM-24	−8.62*	0.14	10.23**	−4.67	−13.80	−48.35*	64.35	55.64**	12.84	9.23	22.58**	0.70	5.10	−15.99	−13.49**	−16.46**	0.00	−14.75**	66.51	38.90
Pusa Basmati-1 × Govindobhog	−3.24	1.62	5.66	−4.04	−8.96	−31.63	44.52	21.26*	−1.51	−11.71	18.52**	14.33*	6.62	−1.01	−10.10**	−19.05**	24.88**	3.82	42.26	18.03
Pusa Basmati-1 × Dehradun Pahari	9.83*	32.99**	−9.40**	−13.03**	24.14	−8.91	16.88	2.60	74.36*	54.55	−2.50	−34.19**	−35.65**	−55.26**	−35.77**	−39.11**	−3.17	−17.30**	66.31	11.45
Pusa Basmati-1 × Gopalbhog	19.49**	41.06**	0.87	−9.35**	79.73**	27.92	9.64	−2.14	54.15*	36.36	29.77**	−6.49	−3.43	−19.74*	−31.22**	−42.71**	−18.56**	−29.55**	39.87	34.48
Pusa Basmati-1 × Tulaipanji	−11.46**	−4.75	−19.77**	−24.82**	−63.17**	−65.65**	45.01	32.71*	−6.57	−24.52	0.44	−31.34**	−9.16	−30.79**	−17.17**	−29.59**	38.16**	29.07**	57.07	13.77
BM-24 × Govindobhog	0.12	4.27	−1.79	−7.01	202.27**	110.90*	−41.45**	−52.97**	−60.98*	−63.96*	−21.41**	−31.51**	−41.43**	−55.69**	−23.30**	−33.05**	−41.52**	−43.27**	−65.21*	−74.94**
BM-24 × Dehradun Pahari	−3.49	5.83	8.13*	−3.04	118.54*	55.66	−20.85	−26.98	141.98**	108.51**	130.62**	78.07**	50.04**	23.96	−34.91**	−42.13**	−22.80**	−22.97**	215.95**	138.41**
BM-24 × Gopal bhog	−5.24	1.49	23.55**	18.30**	98.58	45.83	−29.62*	−40.11**	118.81**	99.30**	25.74*	6.01	−40.73**	−43.58**	−54.84**	−63.42**	−24.31**	−25.62**	−9.23	−21.75
BM-24 × Tulaipanji	2.90	4.70	7.72*	−1.18	28.47	−24.73	38.97	34.02*	−20.40	−34.08	178.90**	119.11**	177.00**	159.69**	−6.44*	−22.72**	−21.53**	−36.75**	15.98	−3.09
Govindobhog × Dehradun Pahari	13.22**	29.74**	−5.82	−11.12**	2.18	−1.72	18.48	−10.40	17.32	−5.41	21.38*	−16.46*	−7.64	−38.37**	−21.64**	−25.80**	−15.06**	−17.77**	−9.91	−44.85
Govindobhog × Gopal bhog	20.49**	34.75**	3.22	2.02	−76.17	−28.03	−15.01	−20.80*	13.58	11.89	−21.35*	−42.01**	−47.35**	−58.74**	−34.98**	−40.45**	−24.68**	−28.16**	−34.05	−46.96*
Govindobhog × Tulaipanji	−22.17**	−20.38**	10.05**	6.41	−1.44	−29.31	−17.92	−35.85**	−21.95	−30.73	−29.96**	−51.14**	−38.85**	−55.70**	−15.17**	−20.49**	16.61**	−8.14**	−16.77	−46.08*
Dehradun Pahari × Gopalbhog	25.55**	28.35**	−14.51**	−20.19**	−46.73	−49.25	−6.38	−25.42*	11.40	−11.19	19.56	7.20	29.18*	2.67	9.84**	−4.25	−11.44**	−12.78**	29.28	−11.53
Dehradun Pahari × Tulaipanji	15.87**	29.47**	17.07**	19.13**	77.39**	24.58	13.40	17.30	31.82	49.72*	91.18**	86.66**	96.85**	71.80**	3.18	8.09*	47.14**	−57.32**	33.35	17.25
Gopalbhog × Tulaipanji	8.34*	18.20**	−3.53	−7.76*	−53.63*	−68.32**	36.74	12.94	−37.89	−44.13*	67.41**	53.39**	39.33**	24.77	−16.65**	−18.69**	8.85*	−11.07**	6.78	−20.66
Range																				
Minimum	**−22.17**	**−20.38**	**−19.77**	**−24.82**	**−76.17**	**−68.32**	**−41.45**	**−52.97**	**−60.98**	**−63.96**	**−29.96**	**−51.14**	**−47.86**	**−61.01**	**−54.84**	**−63.42**	**−41.52**	**−57.32**	**−65.21**	**−74.94**
Maximum	**33.03**	**43.48**	**23.55**	**19.13**	**202.27**	**110.9**	**70.27**	**55.64**	**141.98**	**108.51**	**178.9**	**119.11**	**177**	**159.69**	**9.84**	**8.09**	**47.14**	**29.07**	**215.95**	**138.41**
Average heterosis	**8.49**	**19.64**	**2.09**	**−3.59**	**27.96**	**−1.22**	**13.35**	**1.23**	**14.46**	**2.92**	**37.24**	**13.01**	**18.57**	**1.45**	**−16.62**	**−24.12**	**−1.61**	**−15.57**	**30.49**	**3.42**
No. of crosses with positive heterosis	**14 (12)**	**19 (13)**	**12 (8)**	**7 (2)**	**11 (5)**	**8 (2)**	**14 (7)**	**11 (6)**	**11 (4)**	**9 (3)**	**16 (14)**	**12 (8)**	**12 (9)**	**10 (5)**	**4 (2)**	**2 (1)**	**7 (7)**	**4 (2)**	**14 (3)**	**10 (1)**
No. of crosses with negative heterosis	**7 (3)**	**2 (1)**	**9 (4)**	**14 (8)**	**10 (3)**	**13 (4)**	**7 (2)**	**10 (5)**	**10 (1)**	**12 (2)**	**5 (4)**	**9 (7)**	**9 (6)**	**11 (9)**	**17 (16)**	**19 (17)**	**13 (10)**	**17 (15)**	**7 (1)**	**11 (3)**

*, **, ***Significant at $p = 0.05$, 0.01, and 0.001, respectively. Figures in parenthesis indicate significant values.

Table 9: Frequency of crosses as per GCA effect of parents for economic characters.

Characters	Number of significant heterotic (mp) hybrids and GCA effects of the parents involved			
	High × High	High × Low	Low × Low	Total
Plant height	0	2	1	3
Main panicle length	0	1	7	8
Exsertion length	0	2	3	5
Leaf area	1	2	4	7
Total effective tillers	0	2	2	4
Spikelet number/panicle	1	7	6	14
Filled grain/panicle	0	1	8	9
Fertility (%)	0	1	1	2
Test weight	0	4	3	7
Seed yield/plant	0	1	2	3
Total	**2**	**23**	**37**	**62**
Percentage	**3.23**	**37.09**	**59.68**	**100**

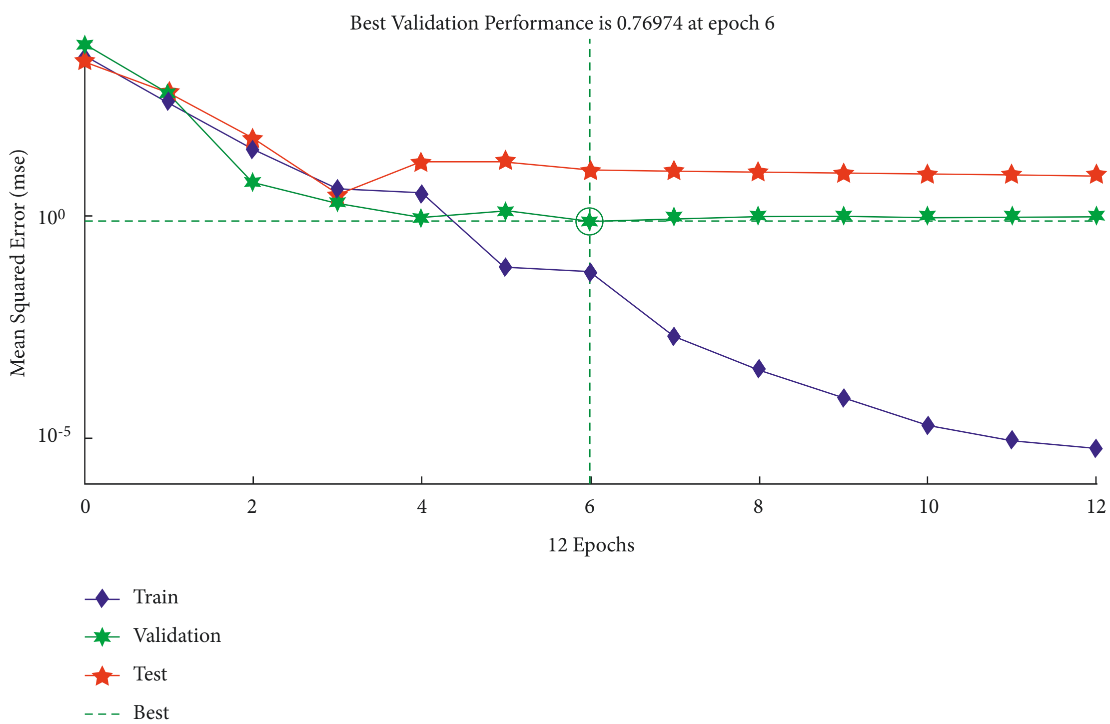

Figure 2: Performance verification using ANN.

combiners (High × High GCA) would involve interaction between positive × positive alleles and can be settled in the succeeding generations due to additive type gene actions which are fixable in nature. Hence, superior segregants could be confined from Pusa Basmati-1 × BM-24 if no repulsion phase linkage is involved and anticipated to throw some useful transgressive segregants in the breeding programme through pedigree method of selection. The result indicated that parental diversity in terms of GCA effect performed an important role for the expression of observed heterosis.

3.6. Validation of Results Using ANN. Both internal and external parameters should be considered. It is not intended to run a variety of algorithms on the available data to determine which one outperforms the others. Although this would be advantageous, and the researchers may consider it in the future, the authors of this work wish to focus on how machine learning techniques, specifically ANN, can be used more successfully in construction management. As a result, this study discusses the problem in broad strokes. In this case, the qualities proposed must first be justified. The ANN

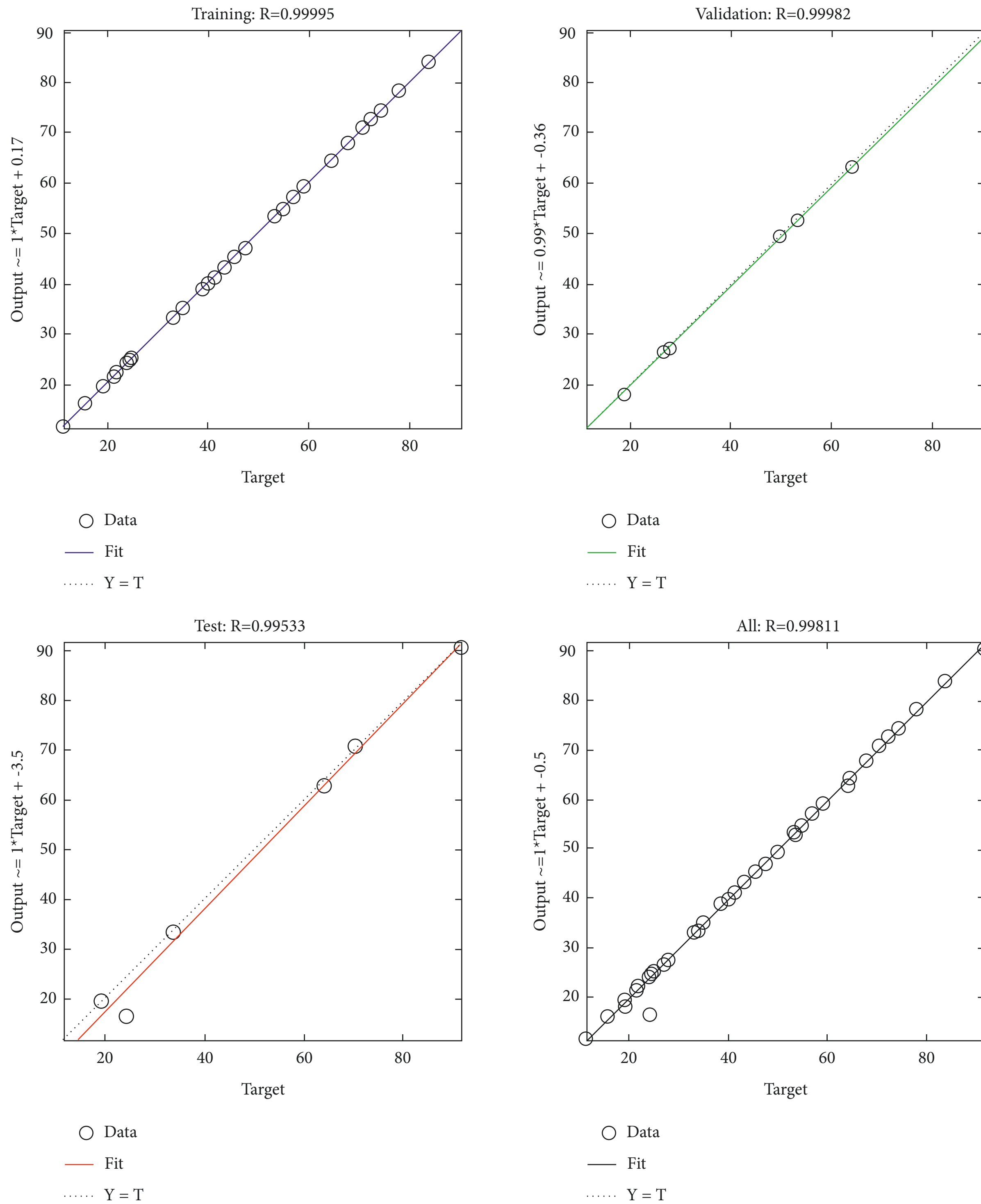

Figure 3: Fit curve with ANN.

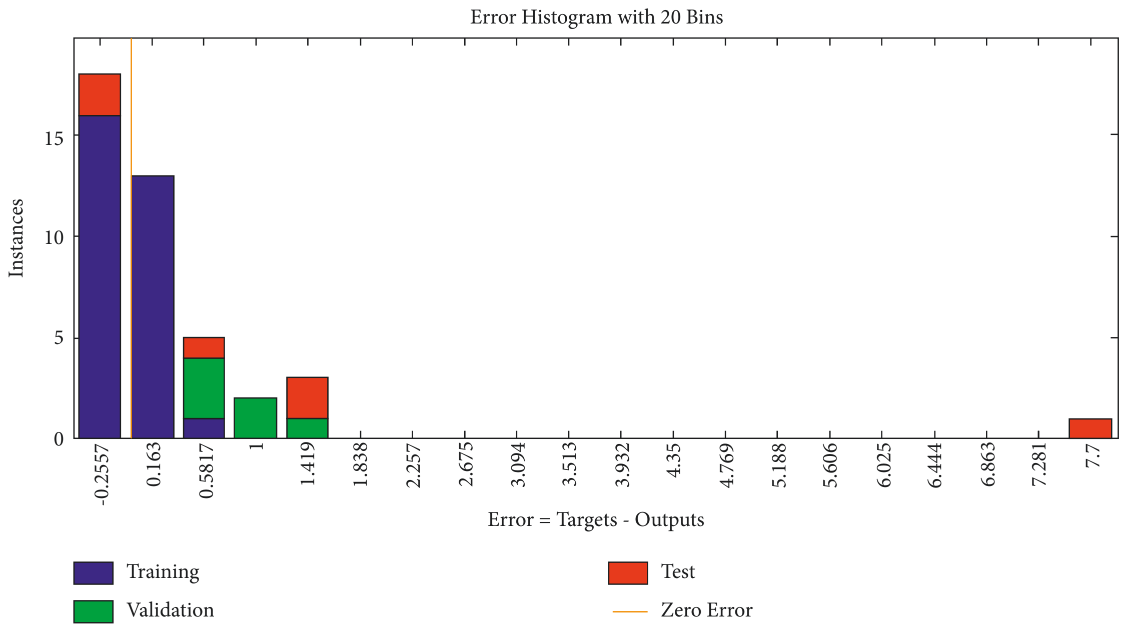

Figure 4: Error histogram of ANN.

Table 10: Effect of hidden layer neuron of validation.

No. of hidden layer neurons	Accuracy obtained (%)
10	94
20	96
30	97
40	97
50	97

model is then presented. In the third step, the features of the accessible database are examined. Finally, the findings are scrutinised and compared to the previous research. ANN is ued as sofisticated tool for verifying and validation of the experimental results. As for the input plant height, panicle length and other parameters are used in Tables 2–4. The initial test was carried out with 10 neuron in the hidden layer with 75% used for training, 15% used for validation, and 15% used for testing. Figure 2 shows the performance indices with the input parameters. The best performance is at epoch 6 with value 0.769. Similarly, the fit cure is shown in Figure 3. All have an accuracy of 99%. And, finally, Figure 4 shows the error histogram.

From Table 10, it is clear that the best hidden layer neuron number is 30.

4. Conclusion

In terms of per se performance, heterosis, and SCA effects for seed yield per plant and other important yield attributes, the crosses BM-24 Dehradun Pahari, Baskota × Tulaipanji, and Pusa Basmati-1 × Tulaipanji are of interest because all of these hybrids had high per se performance and positive heterosis for grain yield. The possibility of obtaining high yielding lines from this cross combination after fixation of additive genetic variance components in advance segregating generation cannot be ruled out. BM-24 and Pusa Basmati-1 used in the present investigation provided ample scope for utilization in the hybridization programme to recombine unique characters such as short stature, high tillering capacity with pleasant aroma, and slender grain size. Some selected F_1 possessed high grain yield with semi-dwarf to medium stature, high tillering behavior, resistance to lodging, and pleasant aroma. However, the better performance of the selection may be due to the presence of heterosis and these selections need further evaluation in segregating generations and elaborate screening and extensive testing. An artificial neural network model of verification and validation yield from transplanting field parameters was designed and trained using experimental data to address the need for a simple and quick validation tool. The constructed ANN model, which has six inputs, two outputs, and ten hidden layers, was proven to be quite capable of learning the relationship.

Data Availability

The data used in this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

The authors are thankful to Visva-Bharati University for providing necessary field and laboratory facilities.

References

[1] N. R. Chakraborty and P. C. Kole, “Gamma ray induced early generations polygenic variability in medium grain aromatic

non-basmati rice," *International Journal of Plant Breeding and Crop Science,*vol. 1, no. 1, pp. 028–035, 2014.
[2] R. K. Sing and U. S. Sing, *Sustainable Agriculture for Food, Energy and Industry*, Routledge, England, UK, 1998.
[3] A. Kant and N. R. Chakraborty, "Induction of mutation through gamma irradiation in non-basmati aromatic "badshabhog" rice (*Oryza sativa* L.)," *Applied Biological Research*, vol. 23, no. 1, pp. 50–59, 2021.
[4] A. Kant, N. R. Chakraborty, and B. K. Chakraborty, "Immediate radiation effects and determination of optimal dose of gamma rays on non-basmati aromatic rice (*Oryza sativa* L.) of eastern India," *Journal of Experimental Biology and Agricultural Sciences*, vol. 8, no. 5, pp. 586–604, 2020.
[5] K. Phasinam, T Kassanuk, and M. Shabaz, "Applicability of internet of things in smart farming," *Journal of Food Quality*, vol. 2022, Article ID 692922, 7 pages, 2022.
[6] A. Singh, G. Vaidya, V. Jagota et al., "Recent advancement in postharvest loss mitigation and quality management of fruits and vegetables using machine learning frameworks," *Journal of Food Quality*, vol. 2022, Article ID 6447282, 9 pages, 2022.
[7] A. Malik, G. Vaidya, V. Jagota et al., "Design and evaluation of a hybrid technique for detecting sunflower leaf disease using deep learning approach," *Journal of Food Quality*, vol. 2022, Article ID 9211700, 12 pages, 2022.
[8] M. Yang, P. Kumar, J. Bhola, and M. Shabaz, "Development of image recognition software based on artificial intelligence algorithm for the efficient sorting of apple fruit," *International Journal of System Assurance Engineering and Management*, vol. 13, no. S1, pp. 322–330, 2021.
[9] R. K. Varshney, A. Bohra, J. Yu, A. Graner, Q. Zhang, and M. E. Sorrells, "Designing future crops: genomics-assisted breeding comes of age," *Trends in Plant Science*, vol. 26, no. 6, pp. 631–649, 2021.
[10] K. Darkwa, B. Olasanmi, R. Asiedu, and A. Asfaw, "Review of empirical and emerging breeding methods and tools for yam (*Dioscorea spp.*) improvement: status and prospects," *Plant Breeding*, vol. 139, no. 3, pp. 474–497, 2020.
[11] R. Khan, N. Tyagi, and N. Chauhan, "Safety of food and food warehouse using VIBHISHAN," *Journal of Food Quality*, vol. 2021, Article ID 1328332, 12 pages, 2021.
[12] S. Katiyar, R. Khan, and S. Kumar, "Artificial bee colony algorithm for fresh food distribution without quality loss by delivery route optimization," *Journal of Food Quality*, vol. 2021, Article ID 4881289, 9 pages, 2021.
[13] S. S. Lakshman, N. Chakrabarty, and P. C. Kole, "Study on the combining ability and gene action in sunflower through line × tester mating design," *Electronic Journal of Plant Breeding*, vol. 10, no. 2, p. 816, 2019.
[14] S. O. Araújo, R. S. Peres, J. Barata, F. Lidon, and J. C. Ramalho, "Lco characterising the agriculture 4.0 landscape-emerging trends, challenges and opportunities," *Agronomy*, vol. 11, no. 4, p. 667, 2021.
[15] S. C. Mukhopadhyay, *Lecture Notes in Electrical Engineering*, Springer, Berlin, Germany, 2012.
[16] N. M. Trendov, S. Varas, and M. Zeng, *Digital Technologies in Agriculture and Rural Areas: Status Report*, Food and Agriculture Organization, Rome, Italy, 2019.
[17] A. Hadidi, D. Saba, and Y. Sahli, *Artificial Intelligence for Sustainable Development: Theory, Practice and Future Applications*, Springer, New York, NY, USA, 2021.
[18] B. Griffing, "Concept of general and specific combining ability in relation to diallel crossing systems," *Australian Journal of Biological Sciences*, vol. 9, no. 4, p. 463, 1956.
[19] G. K. Saini, H. Chouhan, S. Kori et al., "Recognition of human sentiment from image using machine learning," *Annals of the Romanian Society for Cell Biology*, vol. 25, no. 5, pp. 1802–1808, 2021.
[20] S. Mohanasundaram, E. Ramirez-Asis, A. Quispe-Talla, M. W. Bhatt, and M. Shabaz, "Experimental replacement of hops by mango in beer: production and comparison of total phenolics, flavonoids, minerals, carbohydrates, proteins and toxic substances," *International Journal of System Assurance Engineering and Management*, vol. 13, no. S1, pp. 132–145, 2021.
[21] T. K. Lohani, M. T. Ayana, A. K. Mohammed, M. Shabaz, G. Dhiman, and V. Jagota, "A comprehensive approach of hydrological issues related to ground water using GIS in the Hindu holy city of Gaya, India," *World Journal of Engineering*, p. 6, 2021.
[22] S. N. H. Bukhari, A. Jain, E. Haq et al., "Machine learning-based ensemble model for Zika virus T-cell epitope prediction," *Journal of Healthcare Engineering*, vol. 2021, Article ID 9591670, 10 pages, 2021.
[23] S. S. Kargbo, F. Showemimo, P. Akintokun, and J. Porbeni, "Combining ability analysis and gene action for yield and yield-related traits in rice (*Oryza sativa* L.) under saline conditions," *Journal of Plant Breeding and Genetics*, vol. 7, no. 2, pp. 63–74, 2019.
[24] K. P. V. Fels, X. Wei, E. M. Ross et al., "Strategies and considerations for implementing genomic selection to improve traits with additive and non-additive genetic architectures in sugarcane breeding," *Theoretical and Applied Genetics*, vol. 134, no. 5, pp. 1493–1511, 2021.
[25] T. M. Mazal, M. M. ElShnawy, G. B. Anis, and F. A. Hussein, "Genetic analysis of some qualitative and quantitative traits in rice (*Oryza sativa* L.)," *Journal of Plant Production*, vol. 12, no. 5, pp. 577–583, 2021.
[26] B. P. Mallikarjuna, N. Shivakumar, and S. Kukanur, "Combining ability analysis in newly developed rice (*Oryza sativa* L.) hybrids," *Environment and Ecology*, vol. 34, no. 1A, pp. 400–404, 2016.
[27] P. P. Patil, R. D. Vashi, D. A. Shinde, and V. A. Lodam, "Nature and magnitude of heterosis for grain yield and yield attributing traits in rice (*Oryza sativa* L.)," *Plant Archives*, vol. 11, no. 1, pp. 423–427, 2011.
[28] D. A. Bano and S. P. Singh, "Combining ability studies for yield and quality traits in aromatic genotypes of rice (*Oryza sativa.* L.)," *Electronic Journal of Plant Breeding*, vol. 10, no. 2, p. 341, 2019.
[29] N. F. Jenson, "A diallel selective mating system for cereal breeding," *Crop Science*, vol. 10, pp. 628–633, 1970.
[30] G. F. Sprague and L. A. Tatum, "General vs. specific combining ability in single crosses of corn," *Agronomy Journal*, vol. 34, no. 10, pp. 923–932, 1942.
[31] M. S. Abd El-Aty, M. I. Abo-Youssef, A. A. Galal et al., "Genetic behavior of earliness and yield traits of some rice (*Oryza sativa* L.) genotypes," *Saudi Journal of Biological Sciences*, vol. 29, no. 4, pp. 2691–2697, 2022.
[32] N. Rajan, S. Debnath, A. k Dutta et al., "Elucidation of nature of gene action and estimation of combining ability effects for fruit yield improvement and yield attributing traits in brinjal landraces," *Journal of Food Quality*, vol. 2022, Article ID 8471202, 12 pages, 2022.
[33] S. M. Sarsar, R. A. Patil, and S. S. Bhatede, "Heterosis and combining ability in upland cotton," *Indian Journal of Agricultural Sciences*, vol. 56, no. 8, pp. 567–573, 1986.

[34] K. R. Lamkey and J. W. Edwards, “Quantitative genetics of heterosis, the genetics and exploitation of heterosis,” in *Proceedings of the International Symposium on the Genetics and Exploitation of Heterosis in Crops*, pp. 31–48, Mexico City, Mexico, 1999.
[35] J. S. Lee, M. Jahani, K. Huang et al., “Expression complementation of gene presence/absence polymorphisms in hybrids contributes importantly to heterosis in sunflower,” *Journal of Advanced Research*, 2022.
[36] K. R. Devi, K. Parimala, and C. Cheralu, “Heterosis for yield and quality traits in rice (*Oryza sativa* L.),” *Journal of Research ANGRAU*, vol. 42, no. 1, pp. 1–11, 2014.
[37] M. M. Gaballah, K. A. Attia, A. M. Ghoneim et al., “Assessment of genetic parameters and gene action associated with heterosis for enhancing yield characters in novel hybrid rice parental lines,” *Plants*, vol. 11, no. 3, p. 266, 2022.
[38] J. E. Grafius, “Heterosis in Barley 1,” *Agronomy Journal*, vol. 51, no. 9, pp. 551–554, 1959.
[39] J. Y. Peng and S. S. Virmani, “Combining ability for yield and four related traits in relation to breeding in rice,” *Oryza*, vol. 27, pp. 1–10, 1990.
[40] V. V. Casco, R. T. Tapic, J. R. Undan, A. M. L. S. Latonio, R. R. Suralta, and N. L. Manigbas, “Combining ability, floral biology, and seed producibility of promising cytoplasmic male-sterile (CMS) lines for hybrid rice development,” *CABI Agriculture and Bioscience*, vol. 2, no. 1, p. 38, 2021.
[41] G. Anusha, D. S. Rao, V. Jaldhani et al., “Grain Fe and Zn content, heterosis, combining ability and its association with grain yield in irrigated and aerobic rice,” *Scientific Reports*, vol. 11, no. 1, Article ID 10579, 2021.
[42] B. Devi and G. M. Lal, “Combining ability analysis for yield & yield components in rice (*Oryza sativa* L.),” *Electronic Journal of Plant Breeding*, vol. 6, no. 2, pp. 360–365, 2015.
[43] S. Singh and B. S. Choudary, “Combining ability for some metric traits in rice,” *Madras Agricultural Journal*, vol. 82, pp. 165–169, 1995.
[44] T. H. Singh, S. P. Gupta, and P. S. Phul, “Line × tester analysis for combining ability in cotton,” *Indian Journal of Genetics and Plant Breeding*, vol. 31, pp. 316–321, 1971.
[45] K. R. Devi, K. R. Prasad, and P. J. Rao, “Allocytoplasmic restorers and performance of hybrids in rice (*Oryza sativa* L.),” *Electronic Journal of Plant Breeding*, vol. 12, no. 4, pp. 1422–1431, 2021.
[46] E. A. ElShamey, R. M. Sakran, M. A. ElSayed et al., “Heterosis and combining ability for floral and yield characters in rice using cytoplasmic male sterility system,” *Saudi Journal of Biological Sciences*, vol. 29, no. 5, pp. 3727–3738, 2022.