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Development of an Efficient Grading Model for Maize Seedlings Based on Indicator Extraction in High-Latitude Cold Regions of Northeast China

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Abstract: Maize, the world's most widely cultivated food crop, is critical in global food security. Low temperatures significantly hinder maize seedling growth, development, and yield formation. Efficient and accurate assessment of maize seedling quality under cold stress is essential for selecting cold-tolerant varieties and guiding field management strategies. However, existing evaluation methods lack a multimodal approach, resulting in inefficiencies and inaccuracies. This study combines phenotypic extraction technologies with a convolutional neural network–long short-term memory (CNN–LSTM) deep learning model to develop an advanced grading system for maize seedling quality. Initially, 27 quality indices were measured from 3623 samples. The RAGA-PPC model identified seven critical indices: plant height (x_1), stem diameter (x_2), width of the third spreading leaf (x_{11}), total leaf area (x_{12}), root volume (x_{17}), shoot fresh weight (x_{22}), and root fresh weight (x_{23}). The CNN–LSTM model, leveraging CNNs for feature extraction and LSTM for temporal dependencies, achieved a grading accuracy of 97.57%, surpassing traditional CNN and LSTM models by 1.28% and 1.44%, respectively. This system identifies phenotypic markers for assessing maize seedling quality, aids in selecting cold-tolerant varieties, and offers data-driven support for optimising maize production. It provides a robust framework for evaluating seedling quality under low-temperature stress.

Keywords: maize; low temperature stress; seedling quality; phenotypic evaluation indicators; efficient extraction; deep learning



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1. Introduction

Northeast China (NEC), encompassing Heilongjiang, Jilin, and Liaoning provinces, is a pivotal hub for maize production, forming part of the global ‘golden maize belt’ [1]. With a sown area of approximately 6,830,700 hectares, NEC accounts for 30% of China’s total maize area with 32.8% of its production, making its output integral to national food security [2,3]. However, NEC’s high latitude and limited heat resources render it particularly vulnerable to low-temperature spells caused by global climate change, significantly

reducing maize yields [4]. Many researchers have comprehensively investigated the effects of low-temperature cold damage on maize in NEC [5–8]. They concluded that these cold spells primarily affect maize production in the NEC region, particularly in Heilongjiang and northern Jilin provinces. It happens during the early reproductive stage (sowing to the seven-leaf stage) and the late reproductive stage (milk ripening to the maturity stage), posing a critical challenge to agricultural stability.

Numerous studies have demonstrated that maize has heightened sensitivity to low temperatures throughout the initial phases of growth and development (including seed germination, seedling emergence, and nutrient growth). Low-temperature chilling during the period from sowing to germination decreases the activity of various starch-degrading enzymes within maize seeds. This significantly reduces seed germination, delays seedling emergence, and decreases the rate of emergence, thereby hindering the establishment of high-yielding populations [9]. In maize seedlings, low-temperature stress reduces seedling growth vigour, attenuates leaf photosynthesis performance, decreases root number, root length, root dry matter accumulation, and root volume, inhibits plant growth and developmental processes, and affects biomass accumulation and partitioning, which significantly decreases seedling quality [10–13]. Maize seedling growth is significantly inhibited after low-temperature stress, with a significant downward trend in primordial radicle length, plant height, stem base diameter, aboveground fresh weight, root fresh weight, and leaf area [14], and the relative growth rate of the embryonic sheath is significantly higher than that of normal-growing plants [15]. In maize cultivation, high-quality seedlings influence the production system's yield, quality, and efficiency [16,17]. Therefore, the quality of maize seedlings should be assessed during production to determine the impacts of unfavourable weather conditions on maize growth, development, and yield. This facilitates the prompt execution of technical strategies to regulate coldland maize challenges and improve the overall standardisation and refinement of maize production management. Manual identification is the primary traditional technique for evaluating the quality of maize seedlings. Traditional methods for seedling quality evaluation rely on manual phenotype assessment, which is time-consuming, labour-intensive, and prone to inconsistencies [11,18]. Thus, a systematic, straightforward, and efficient method for evaluating the quality of maize seedlings is essential to advance superior maize populations and achieve consistently high yields.

Recent advancements in deep learning (DL) offer promising solutions for overcoming these limitations. DL algorithms, such as convolutional neural networks (CNNs) [19], long short-term memory (LSTM) networks [20], recurrent neural networks (RNNs) [21], and generative adversarial networks (GANs) [22], have been utilised in agronomy research. Hao et al. [23] classified leaves into four categories based on variations in the fresh weight of the aerial portion. They developed a hierarchical fusion CNN architecture using multiscale inputs to assess stress levels in lettuce leaves, achieving a classification accuracy of 87.95%. Maginga et al. [24] used non-visual measurements of total volatile organic compounds (VOCs) and ultrasonic emissions from maize plants to detect northern leaf blight (NLB) with a hybrid CNN–LSTM model, achieving an accuracy of 0.9639 and an F1 score of 0.96. This method shows great potential for early disease detection in maize. Zhuang et al. [25] employed a CNN to detect early water stress in maize by categorising different water stress levels (well-watered, less-watered, and drought-stressed) using original images of maize plants in their natural environments. They identified three types of maize water stress states, achieving a recognition accuracy of 88.41% and providing scientific guidance for early irrigation of maize. Numerous studies have graded plant quality after crop stress using DL techniques with high accuracy and feasibility to provide a reference for precision agriculture. However, these studies only identified individual organs or specific plant

indices and did not comprehensively monitor or holistically grade crop seedling quality indices. Moreover, the use of DL methodologies to assess the overall quality of maize seedlings during grading has rarely been recorded. Therefore, to address the gap in the novel grading evaluation system for maize seedlings, this study presents a methodology for evaluating coldland maize seedlings by extracting seedling quality traits and using DL algorithms.

We use ‘Xianyu 335’, a primary maize variety that is widely planted in NEC, as the test material. We use a large-scale artificial climate chamber that can realise temperature changes and soil potting methods. We measure 27 quality indices of maize seedlings and calculated comprehensive evaluation indices of maize seedling quality using the projection tracing classification model. A thorough assessment metric for seedling quality is determined by using a projection-tracing classification technique. A correlation analysis between each quality index of maize seedlings and a comprehensive evaluation index is conducted, and several representative quality indices are screened. We then construct a cascaded CNN–LSTM model and combine the seedling quality index extraction technique with DL. Subsequently, a grading technique for coldland maize seedlings is developed, utilising seedling quality phenotype extraction and DL to achieve a rapid and precise assessment of seedling quality. We establish a theoretical foundation for essential technologies related to maize yield mechanisation and efficiency in cold regions, enhance management strategies during the maize seedling stage, improve disaster prevention and mitigation capabilities, and facilitate scientific and rational responses to climate change.

2. Materials and Methods

2.1. Test Material

We use the ‘Xianyu 335’ maize variety (bred by Tieling Pioneer Seed Research Co., Ltd., Tieling, China), a prevalent and promoted cultivar in the high-latitude cold regions of NEC. The research soil was sourced from the 0–20 cm plough layer of the Anda Agricultural Science and Technology Park at Heilongjiang Bayi Agricultural University. This soil had a pH of 8.06, an organic matter content of 26.59 g kg^{−1}, an alkali-hydrolysed nitrogen content of 104.46 mg kg^{−1}, an available phosphorus content of 11.47 mg kg^{−1}, and an available potassium content of 113.73 mg kg^{−1}. The dirt was desiccated, pulverised, and filtered through a 5 mm sieve. Plastic buckets measuring 38 cm in height and 40 cm in diameter were used in the pot experiment.

2.2. Experimental Design

From 2019 to 2021, a pot experiment was conducted at the Key Laboratory of Modern Agricultural Cultivation Technology and Crop Genetic Improvement in Heilongjiang Province (Daqing, Heilongjiang, China). The region is located in the north temperate continental monsoon climate zone, with an average annual temperature of −5 to 10 °C and an average annual precipitation of approximately 400 mm–700 mm [26,27]. The pot experiment was designed using three variables: low-temperature treatment stage, temperature level for low-temperature treatment, and duration of low-temperature treatment. Based on the meteorological data from typical maize-planting ecological areas in the high-latitude cold region of Northeast China over the past 10 years [28], we fitted the daily temperature variation trend of the 0–5 cm topsoil from maize sowing to seedling stage. Considering these conditions, we dynamically simulate the temperature environment for maize growth from sowing to seedling stage and synchronously set low-temperature environments of 0, 2, 4, 6, 8, and 10 °C (Figure 1) [29]. The low-temperature treatment stage comprised six intervals: 1–5 days post-sowing (P1), 6–10 days (P2), 11–15 days (P3), 16–20 days (P4), 21–25 days (P5), and 26–30 days (P6). The low-temperature treatment comprised six levels,

0, 2, 4, 6, 8, and 10 °C, while the duration of low-temperature exposure was categorised into six levels, 0 (D0), 1 (D1), 2 (D2), 3 (D3), 4 (D4), and 5 (D5) days, with 0 days (D0) serving as the control at ordinary temperature. Each treatment was set up with ten replicates in a completely random arrangement, and pot rearrangement was performed regularly. The two-year pot experiments were conducted in late April, with ten plants sown in each pot. Following seeding, a standardised irrigation process was implemented, after which the specimens were placed in an artificial environmental chamber for low-temperature simulation studies. After completion of each treatment combination, the potted plants were placed in a natural field setting for continued cultivation. On the 35th day after sowing, four pots from each treatment combination were chosen, and two representative plants from each pot were selected to assess several seedling quality indicators. Subsequently, the six remaining pots of each treatment combination were trimmed, retaining one plant per pot. Yield per maize plant was examined during the maturation phase. We administered 2.83 g of pure nitrogen, 1.47 g of phosphorus pentoxide, and 1.13 g of potassium oxide to the soil in each pot, using 30% of the pure nitrogen along with all phosphorus and potassium fertilisers as a base fertiliser, while 70% of the pure nitrogen was utilised as the top dressing during the V6 stage. All other management practices remained consistent with field production.

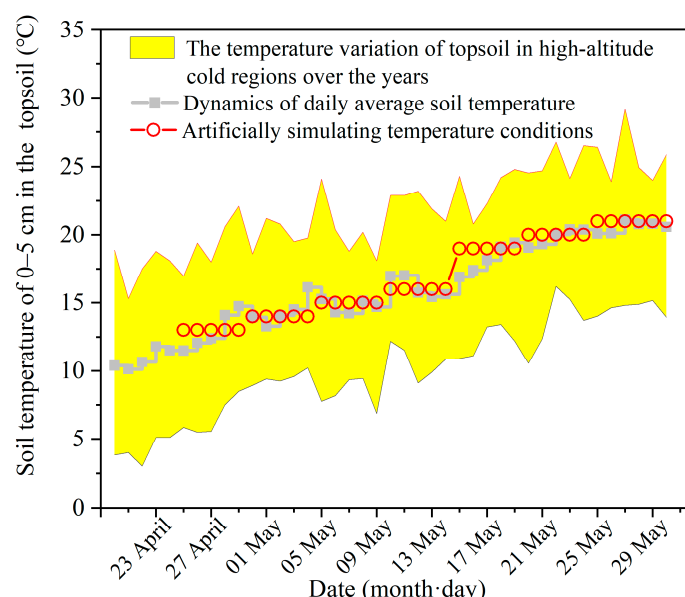


Figure 1. Changing trend of average daily topsoil temperature in spring and the artificial simulated temperature conditions.

2.3. Measurement Items and Methods

Based on previous studies regarding crop seedling quality [16,28,30,31] and considering the growth characteristics of maize along with the principles of practicality and operability, we formulated 27 indicators of seedling quality (Table 1).

Table 1. Twenty-seven seedling quality indicators and numbers.

Quality Indicators of Seedlings	Number	Quality Indicators of Seedlings	Number	Quality Indicators of Seedlings	Number
Plant height	x_1	3rd leaf length	x_{10}	F_0	x_{19}
Stem diameter	x_2	3rd leaf width	x_{11}	F_m	x_{20}
Coleoptile length	x_3	Total leaf area	x_{12}	F_v/F_m	x_{21}

Table 1. Cont.

Quality Indicators of Seedlings	Number	Quality Indicators of Seedlings	Number	Quality Indicators of Seedlings	Number
1st leaf sheath length	x_4	Primary radicle length	x_{13}	Shoot fresh weight	x_{22}
2nd leaf sheath length	x_5	Primary radicle diameter	x_{14}	Root fresh weight	x_{23}
1st leaf length	x_6	Secondary radicle number	x_{15}	Residual seed fresh weight	x_{24}
1st leaf width	x_7	Nodal root number	x_{16}	Shoot dry weight	x_{25}
2nd leaf length	x_8	Root volume	x_{17}	Root dry weight	x_{26}
2nd leaf width	x_9	SPAD value	x_{18}	Residual seed dry weight	x_{27}

Note: F_0 is initial fluorescence, F_m is maximum fluorescence, and F_v is the difference between F_m and F_0 : $F_v = F_m - F_0$.

2.3.1. Determination of Seedling Phenotype Indicators

The dirt around the roots of the collected seedlings was meticulously washed with distilled water, and the excess moisture was absorbed using absorbent paper. Subsequently, the height of the plant (x_1), coleoptile length (x_3), the 1st leaf sheath length (x_4), the 2nd leaf sheath length (x_5), the 1st leaf length (x_6), the 1st leaf width (x_7), the 2nd leaf length (x_8), the 2nd leaf width (x_9), the 3rd leaf length (x_{10}), the 3rd leaf width (x_{11}), and the stem diameter (x_2) were measured using vernier callipers. Total leaf area (x_{12}) was calculated using the aspect coefficient method, and the primary radicle length (x_{13}), primary radicle diameter (x_{14}), secondary radicle number (x_{15}), nodal root number (x_{16}), and root volume (x_{17}) were assessed using the WinRHIZO Pro root analysis system (Zealquest Scientific Technology Co., Ltd., Shanghai, China) [32]. After measuring the aforementioned indices, the plants were categorised as aboveground, belowground, or residual seeds. The fresh weights of shoots (x_{22}), roots (x_{23}), and residual seeds (x_{24}) were recorded. The samples were then enclosed in a Kraft paper bag and exposed to a temperature of 105 °C for 30 min, after which they were dried at 80 °C until a constant weight was attained. The dry weights of shoots (x_{25}), roots (x_{26}), and residual seeds (x_{27}) were quantified.

2.3.2. Determination of SPAD Value and Fluorescence Parameters of Leaves

At 35 days post-sowing, the most recent fully expanded leaves devoid of pests, illnesses, physiological abnormalities, or mechanical injuries were collected. The chlorophyll content (x_{18}) of the upper, middle, and lower leaf sections was quantified using a SPAD-502 Plus chlorophyll analyser (Konica Minolta Holdings, Inc., Tokyo, Japan), and the mean value was recorded [33,34]. A chlorophyll pulse-make fluorescence analyser OS-30p (Opti-Sciences, Inc., Hudson, NY, USA) was then used to measure the fluorescence parameters of the leaves after they had been dark-adapted for 30 min. The initial fluorescence, F_0 (x_{19}), was measured at the top, middle, and bottom of the leaves. Once F_0 had stabilised, the saturated pulsed light was irradiated to obtain the maximum fluorescence, F_m (x_{20}), and the maximum photochemical efficiency, F_v/F_m (x_{21}), $F_v/F_m = (F_m - F_0)/F_m$, was calculated.

2.3.3. Calculation of Yield per Plant and Classification of Seedling Quality Classes

All plants from each treatment combination were manually plucked at maturity to assess seed production. A PM-8188-A grain moisture meter (Kett Electric Laboratory Co. Ltd., Tokyo, Japan) was used to measure the kernel weight of five randomly selected maize plants from each treatment, quantify the kernel moisture content, and standardise the final kernel yield to 14.0% moisture content [35]. According to the seedling quality-grading method in the literature [36], we classified those with single-plant yields between 225.82 and 287.19 g as the optimal seedling grade (I), those between 186.69 and 225.82 g as the suboptimal seedling grade (II), those between 118.93 and 186.69 g as the medium seedling grade (III), and those between 80.56 and 118.93 g as the weak seedling grade (IV).

2.4. Screening of Seedling Quality Indicators

According to previous methods [37,38], 27 maize seedling quality indices were comprehensively analysed using a projection pursuit classification (PPC) model based on a genetic algorithm (GA) to calculate the projection value of the overall quality of maize seedlings. Correlation analysis was performed between each maize seedling quality index and the comprehensive evaluation index, and several representative quality indices were screened to establish a maize seedling grading model.

2.4.1. GA-PPC Model Building

Projection Pursuit Model

The PPC model examines high-dimensional data properties by projecting them into a low-dimensional subspace and analysing the projected eigenvalues that may represent the structure or features of the original data. The following steps comprise the modelling process of the PPC model:

Step 1: Normalise the sample assessment indicator set. Designate the sample set for each indicator value to be $\{x^*(i, j) | i = 1 \sim n, j = 1 \sim p\}$, where $x^*(i, j)$ is the j th indicator value of the i th maize seedling sample, and n and p are the quantity of seedling samples (sample capacity) and the number of indicators, respectively. Normalise the data to standardise the range of variation in each indicator's values and remove the bias caused by the various scales of the data for each indicator:

$$x(i, j) = \frac{x^*(i, j) - x_{\min}(j)}{x_{\max}(j) - x_{\min}(j)}, \quad (1)$$

where $x(i, j)$ is the series of normalised indicator eigenvalues, and $x_{\max}(j)$ and $x_{\min}(j)$ are the highest and lowest values of the j th indicator, respectively.

Step 2: Construct the projection index function $Q(a)$, that is, the 27-dimensional data $\{x^*(i, j) | j = 1 \sim p\}$ of the maize seedling quality evaluation index system constructed in this study, combined with the projection direction $a = \{a(1), a(2), a(3), \dots, a(p)\}$, to obtain the one-dimensional projection value as follows:

$$z(i) = \sum_{j=1}^p a(j)x(i, j) \quad (i = 1 \sim n). \quad (2)$$

A one-dimensional scatter plot with $\{z(i) | i = 1 \sim n\}$ was used as the basis for classification. a is the unit-length vector in Equation (2). The scattering characteristics of the projection values $z(i)$ must be as follows when synthesising the projection indicator values. Overall, the projected point clusters must be as dispersed from one another as possible, while locally, the projected points must be maximally dense, ideally coalescing into multiple point clusters. Consequently, the projection index function can be expressed as follows [39]:

$$Q(a) = S_z D_z, \quad (3)$$

where S_z is the standard deviation of the projected value $z(i)$ and D_z is the local density of the projected value $z(i)$, as follows:

$$S_z = \sqrt{\frac{\sum_{i=1}^n (z(i) - E(z))^2}{n - 1}} \quad (4)$$

$$D_z = \sum_{i=1}^n \sum_{j=1}^n (R - r(i, j)) \cdot u(R - r(i, j)) \quad (5)$$

In this context, $E(z)$ represents the mean value of the sequence $\{z(i) \mid i = 1 \sim n\}$; R denotes the window radius of the local density, selected to ensure that the mean quantity of projection points within the window remains sufficiently large to prevent excessive sliding average deviation while avoiding an excessive increase with the growth of n . R is often regarded as $0.1 S_z$. $r(i, j)$ is the distance between the samples, defined as $r(i, j) = |z(i) - z(j)|$; $u(t)$ is the unit step function, which equals 1 when $t \geq 0$ and 0 when $t < 0$.

Step 3: Enhance the projection metric function. When the sample set for each metric value is provided, the projection metric function $Q(a)$ depends solely on the projection direction a . Various projection directions reveal the distinct structural characteristics of the data, and the optimal projection direction most effectively emphasises a particular feature structure of high-dimensional data. Consequently, the optimal projection direction can be determined by addressing the maximisation problem of the projection index function, as follows:

Maximising the objective function:

$$\text{Max}Q(a) = S_z \cdot D_z. \quad (6)$$

Binding conditions:

$$\text{s.t.} \sum_{j=1}^p a^2(j) = 1. \quad (7)$$

This is a complex nonlinear optimisation problem with $\{a(j) \mid j = 1 \sim p\}$ as the optimisation variable, which is challenging to address using conventional optimisation methods. This study employs a GA that emulates natural selection and chromosomal information transfer within a population to address the high-dimensional global optimisation problem.

Step 4: Classification. The projection value $z^*(i)$ for each sample point can be obtained by substituting the optimal projection direction a^* obtained in Step 3 into Equation (2). Comparing $z^*(i)$ and $z^*(j)$, the closer they are, the more samples i and j fall into the same category. If the samples are sorted by the $z^*(i)$ value from largest to smallest, they can be sorted from best to worst.

Constructing a Genetic Optimisation Algorithm

The GA is an adaptive global optimisation probabilistic search algorithm [40] that simulates the hereditary and evolutionary processes of organisms in the natural environment, which mainly includes the operations of selection, crossover, and mutation. GAs are commonly used to solve complex nonlinear optimisation problems and reduce computational complexity. Its modelling included the following steps:

Step 1: Generate N sets of uniformly distributed random variables $V_i^{(0)}(x_1, x_2, \dots, x_j, \dots, x_p)$ in the interval of variation of the values of each decision variable $[a_j, b_j]$, abbreviated as $V_i^{(0)}$, $i = 1 \sim N$, $j = 1 \sim p$, N is the population size, and p is the number of optimisation variables.

Step 2: Determine the value of the objective function. Replace the initially formed chromosome $V_i^{(0)}$ from Step 1 with the objective function, calculate the associated function value $f^{(0)}(V_i^{(0)})$, and arrange the chromosomes based on the magnitude of the function value to create $V_i^{(1)}$.

Step 3: Define the fitness evaluation function as $\text{eval}(V)$. Establish the likelihood of chromosomes within the population using the fitness assessment function with the parameter $a \in (0, 1)$. The fitness evaluation function was defined as follows:

$$\text{eval}(V) = a(1 - a)^{i-1}, i = 1, 2, \dots, N. \quad (8)$$

Step 4: Select the subsequent generations of humans for manipulation. Each revolution of the betting wheel N times results in selecting a new set of chromosomes, determined by the fitness of each chromosome. This yielded a novel population called $V_i^{(2)}$.

Step 5: Perform a crossover operation on the new population generated in Step 4. Define the parameter P_c as the probability of the crossover operation, denote the parents by V_1' and V_2' , and use the arithmetic crossover method to first generate a random number c from the open interval $(0, 1)$. Perform the crossover operation between V_1' and V_2' to generate the offspring X and Y . $X = c \cdot V_1' + (1 - c) \cdot V_2'$, $Y = (1 - c) \cdot V_1' + c \cdot V_2'$, and after the crossover operation, a new population $V_i^{(3)}$ is generated.

Step 6: Execute a mutation operation on the newly created population from Step 5. Designate the parameter P_m as the probability of mutation. Execute the mutation as outlined. Select the mutation direction d in R'' at random. If $V + Md$ is infeasible, assign M a random value between 0 and M until feasibility is achieved. M represents a suitably large quantity. If a viable solution is not identified within a predetermined number of repetitions, assign $M = 0$ and consistently substitute V with $X = V + Md$, irrespective of the value of M . A new population $V_i^{(4)}$ is produced following the mutation process.

Step 7: Evolutionary progression. The progeny chromosomes derived from Steps 4 to 6 are organised based on their fitness function values in descending order. Subsequently, the algorithm reverts to Step 3 to commence the next iteration of the evolutionary process, which involves re-evaluation, selection, and cross-mutation of the parent population, continuing until the final evolutionary iteration is achieved.

Optimise the projection indicator function $Q(a)$ within the PPC model, which is the objective function. Utilise the projection $a(j)$ of each indicator as the optimisation variable and execute the aforementioned seven steps to determine the optimal projection direction $a(j)$ and the associated projection value $z(i)$.

2.4.2. Correlation Analysis of Individual Quality Indicators with Projected Values

The evolutionary algorithm-based projection tracing model can transform high-dimensional data into a low-dimensional space, determine the ideal projection direction that accurately reflects the structure or properties of high-dimensional data, and use this direction to assess the contribution of each evaluation index to the overall evaluation objective. This approach effectively mitigates the dimensionality curse inherent in high-dimensional data and efficiently removes the influence of irrelevant variables unrelated to the data structure and features [41,42]. Using a data matrix comprising 3623 rows and 27 columns, a projection-seeking model was established. The specific parameters of the model were set as follows: population size $n = 400$, crossover probability $pc = 0.80$, mutation probability $pm = 0.80$, number of outstanding individuals selected as 20, $a = 0.05$, and acceleration number as 20. This yielded an optimal projection direction $a = (0.0409, 0.1368, 0.1334, 0.1832, 0.1999, 0.1608, 0.1698, 0.2266, 0.1498, 0.2360, 0.1626, 0.3210, 0.1165, 0.1375, 0.1621, 0.1178, 0.2890, 0.1245, 0.0937, 0.1157, 0.1094, 0.2733, 0.3021, 0.1123, 0.1866, 0.2345, 0.0648)$ to determine the projected values for the comprehensive evaluation of seedling quality across each low-temperature treatment stage and duration combination.

To address the practical implementation of field production and evaluate the quality of maize seedlings accurately and conveniently, we assessed individual seedling quality indices and analysed their correlation with the comprehensive evaluation projection value ($z(i)$). We identified several representative, simple, and easy-to-obtain quality indices [37] and constructed a simple, practical, and easy-to-operate grading model for maize seedling quality.

From Table 2, plant height (x_1), stem diameter (x_2), coleoptile length (x_3), 1st leaf sheath length (x_4), 2nd leaf sheath length (x_5), 1st leaf length (x_6), 1st leaf width (x_7), 2nd

leaf length (x_8), 2nd leaf width (x_9), 3rd leaf length (x_{10}), 3rd leaf width (x_{11}), total leaf area (x_{12}), root volume (x_{17}), shoot fresh weight (x_{22}), root fresh weight (x_{22}), shoot dry weight (x_{25}), and root dry weight (x_{26}) were highly significantly correlated with the combined evaluation projections. The number of secondary radicles (x_{15}) was significantly correlated while the number of nodal roots (x_{16}), residual seed fresh weight (x_{24}), and residual seed dry weight (x_{27}) were negatively correlated. For operability and convenience in practical production and application, we selected seven single quality indices, plant height (x_1), stem diameter (x_2), the 3rd leaf width (x_{11}), total leaf area (x_{12}), root volume (x_{17}), shoot fresh weight (x_{22}), and root fresh weight (x_{23}), which are closely related to the comprehensive evaluation projected value based on the maize seedling quality evaluation.

Table 2. Correlation between single indicators and comprehensive evaluation projection value.

Single Indicator	Projection Value	Single Indicator	Projection Value
Plant height (x_1)	0.85 **	Secondary radicle number (x_{15})	0.30 *
Stem diameter (x_2)	0.84 **	Nodal root number (x_{16})	−0.39 *
Coleoptile length (x_3)	0.63 **	Root volume (x_{17})	0.72 **
1st leaf sheath length (x_4)	0.65 **	SPAD value (x_{18})	0.01
2nd leaf sheath length (x_5)	0.63 **	F_0 (x_{19})	−0.11
1st leaf length (x_6)	0.54 **	F_m (x_{20})	−0.13
1st leaf width (x_7)	0.64 **	F_v/F_m (x_{21})	−0.06
2nd leaf length (x_8)	0.68 **	Shoot fresh weight (x_{22})	0.84 **
2nd leaf width (x_9)	0.63 **	Root fresh weight (x_{23})	0.76 **
3rd leaf length (x_{10})	0.56 **	Residual seed fresh weight (x_{24})	−0.46 *
3rd leaf width (x_{11})	0.86 **	Shoot dry weight (x_{25})	0.65 **
Total leaf area (x_{12})	0.88 **	Root dry weight (x_{26})	0.65 **
Primary radicle length (x_{13})	0.23	Residual seed dry weight (x_{27})	−0.47 *
Primary radicle diameter (x_{14})	−0.24		

*** indicates that $z(i)$ is highly significantly correlated with a single indicator at the 0.01 level. ** indicates that $z(i)$ is significantly correlated with a single indicator at the 0.05 level.

3. Results

3.1. Construction of a CNN–LSTM-Based Maize Seedling Quality-Grading Model

DL is a novel research trajectory within artificial intelligence, achieving significant advancements in various applications, including natural language processing, pattern recognition, and other recognition and classification capabilities across diverse domains [43]. A CNN is a type of deep feedforward neural network distinguished by local connections and weight sharing. Simultaneously, a CNN possesses a robust self-learning capability, enabling it to learn from the original data autonomously and employ convolutional and pooling layers to extract local features, thereby minimising the parameter count and computational complexity [44,45]. LSTM networks possess long-term memory capacities, enabling them to integrate memory information from both the present and historical stages to generate predictions, effectively addressing the shortcomings of traditional neural networks that cannot fully utilise historical information data [46,47]. This study presents a maize seedling quality-grading model (CNN–LSTM) that integrates CNN and LSTM networks, utilising a two-tier DL framework based on maize phenotypic parameters, where the first tier employs a CNN and the second tier utilises an LSTM, as shown in Figure 2. The CNN–LSTM cascade model integrates the representational learning capabilities of the CNN network with the long-term memory capabilities of the LSTM network, enabling accurate classification of maize seedling quality.

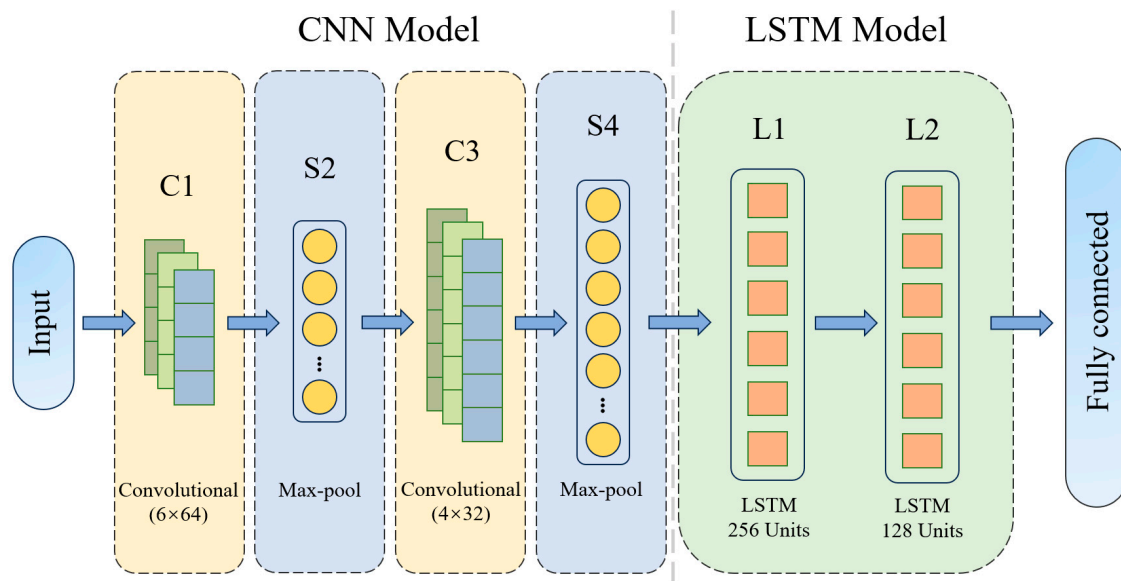


Figure 2. CNN-LSTM network structure.

3.1.1. CNN Network Architecture

The CNN architecture comprises three primary components: convolutional, pooling, and fully connected layers. Based on this, the principle of weight sharing was used to significantly reduce the number of parameters in the model. The pooling layer consolidates the analogous features, thereby decreasing the data volume for training. Moreover, CNNs have three major advantages: local connectivity, weight sharing, and spatial pooling. The computational procedure for each layer in the CNN structure is as follows.

The convolutional layer extracts features from the input data, and an increased number of convolutional kernels results in the extraction of additional features. The C1 convolutional layer, comprising a sequence of learnable convolutional kernels and serving as the fundamental component of the CNN, receives a data input layer that includes seven quality indicators for 3623 seedlings. The convolutional layer extracts feature and reduces data volume; this study employed ‘padding = same’ to guarantee that the output feature matrix of the convolutional layer corresponds in size to the input feature matrix. The convolution kernel sizes of C1 and C3 were configured as 64 and 32, respectively, and the convolution window dimensions were set as 6 and 4, respectively. The convolution operation was executed based on specified kernel sizes and window dimensions. The convolution operation is defined as follows:

$$y^j = f\left(\sum_i k^{ij} * x^i + b^j\right), \quad (9)$$

where y^j and x^i represent the i th input feature and j th output feature, respectively, $*$ represents the convolution operation, k^{ij} specifies the convolution kernel utilised in this layer, and b^j is the bias for the j th feature. The ReLU activation function is employed for nonlinear operations, and its expression is as follows:

$$f(x) = \max(0, x) \quad (10)$$

Pooling layer: The S2 pooling layer was included in the convolutional layer. The pooling layer diminishes data dimensionality, executes secondary feature extraction, and

subsamples data based on local correlation principles to decrease the data volume and improve the neural network's robustness [48]. The formula for the calculation is as follows:

$$s_j^{l+1} = f(\alpha_j^l \text{down}(y_j^l) + b_j^{l+1}), \quad (11)$$

where $\text{down}(\cdot)$ signifies the subsampling function, and α_j^l and b_j^{l+1} represent the j th layer weighting and bias coefficients, respectively. To prevent overfitting, a dropout layer was incorporated following the pooling layer to randomly deactivate neurones at a rate of 0.1, thereby accelerating model convergence and improving generalisation.

A fully linked layer implies that each neuron is interconnected with every neuron in the preceding layer. The fully connected layer employs a SoftMax function, which processes the output from the network to the fully connected layer for categorisation. This output was converted into a feature vector of length 4 through matrix operations pertaining to the four grades of seedling quality. The output vector is then transformed into a representation of the classification probability for each class [49] using the SoftMax function. The SoftMax function is expressed as follows:

$$\text{softmax} = \frac{\exp(z_i)}{\sum_j \exp(z_j)}, \quad (12)$$

where z is the input vector, and i and j each represent one of the elements.

3.1.2. LSTM Network Structure

The LSTM network enhances the RNN by incorporating a forgetting gate, input gate, and output gate structure such that important information can be memorised and unimportant information can be forgotten, and the dependency relationship between time-series data with longer distances is established [50]. It can overcome the problem of disappearing or exploding gradients, and it effectively addresses the correlation problems of time-series data. Figure 3 illustrates the structure of the LSTM network.

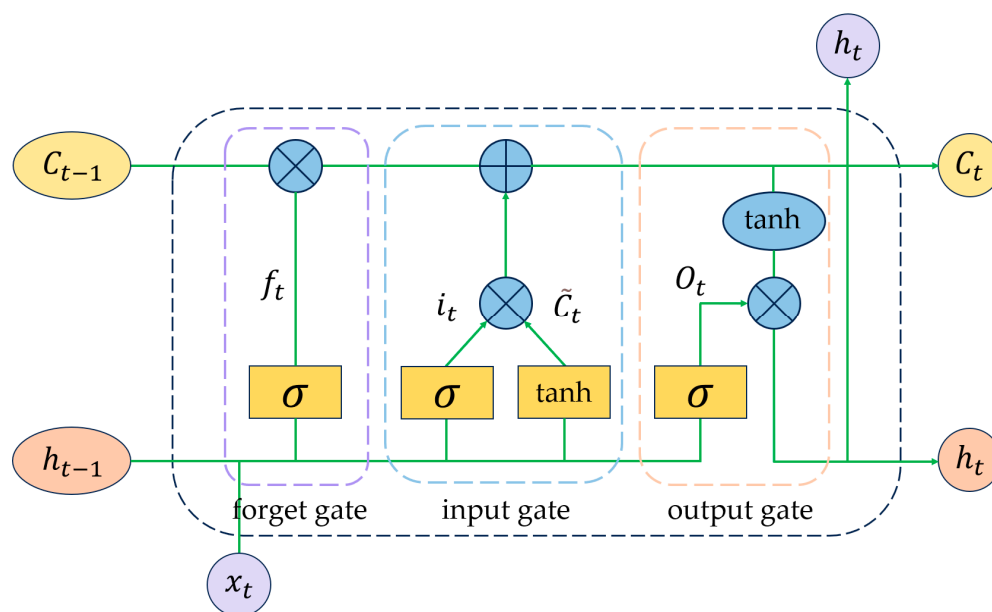


Figure 3. LSTM network structure.

The LSTM network comprises three parts: forget, input, and output gates. The computational process for each layer in the LSTM network architecture is as follows.

1. Forget Gate. It is used to regulate the information in the memory unit from the preceding time step, which requires elimination. Using the forget gate, the LSTM unit can forget previous irrelevant information and retain only useful information. The forget gate assesses the h_{t-1} and x_t , when $f_t = 0$, and the information is discarded; however, when $f_t = 1$ is used, the information is preserved. The formula for f_t is

$$f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f), \quad (13)$$

where W_f represents the weight of the forget gate, σ signifies the activation function, and b_f defines the bias factor for the forget gate.

2. Input Gate. It retains new information within the long-term state, comprising three components: initially, the $\tanh$ layer generates a new vector of candidate values; subsequently, the input gate layer i_t regulates the elements requiring updates; and ultimately, the new information is incorporated into the long-term state, represented by the following formula:

$$\tilde{C}_t = \tanh(W_{cx}x_t + W_{ch}h_{t-1} + b_c), \quad (14)$$

$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i), \quad (15)$$

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t, \quad (16)$$

where $\tilde{C}_t$ denotes the candidate value generated by the $\tanh$ layer, W_{cx} and W_{ch} are the weight matrices of the memory cells, and b_c is the bias coefficient of the memory cells. W_{ix} and W_{ih} denote the weight matrices of the input gates, σ denotes the activation function, b_i denotes the bias coefficients of the input gates, x_t is the input, and h_{t-1} is the output.

3. Output Gate. It regulates information retrieved from the memory cell for the current output. Initially, the output information is ascertained by the sigmoid layer, followed by processing of the long-term state by the layer, which is multiplied by the information filtered through the output gate to yield the final result. The output vector of the output gate is computed as

$$o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o), \quad (17)$$

$$h_t = o_t \tanh(C_t), \quad (18)$$

where σ denotes the sigmoid activation function; W_{ox} and W_{oh} are the weight matrices of the output gates; and b_o is the bias coefficient of the output gates.

Thus, the LSTM completes one iteration and computes the output h_t and the memory cell C_t at the current moment. LSTM regulates the influence of prior information via the forget gate, the influence of current information via the input gate, and the ultimate output through the output gate.

3.1.3. Optimiser

This study presents a seedling quality evaluation model that employs the *Adam* optimiser to determine the optimal network parameters. This optimiser employs first- and second-order moment estimations of gradients to dynamically modify the learning rate associated with each parameter [51], which can accelerate convergence and improve model performance. This study illustrates the parameter update process of *Adam's* method using pseudocode. Algorithm 1 presents the computational procedure of *Adam's* algorithm.

Algorithm 1: Adam optimiser**Input:** $\alpha, \beta_1, \beta_2 \in [0, 1), \theta_0, \lambda$ **Initialise:** $m_0 \leftarrow 0, v_0 \leftarrow 0, t \leftarrow 0$ **While** θ_t *unconverged* **do** $i \leftarrow i + 1$ $g_i \leftarrow g_i + \lambda \theta_{i-1}$ $\triangleright g_i$ was the gradient of the time step $m_i \leftarrow \beta_1 \cdot m_{i-1} + (1 - \beta_1) \cdot g_i$ $\triangleright m_i$ was the first moment of the step $v_i \leftarrow \beta_2 \cdot v_{i-1} + (1 - \beta_2) \cdot g_i^2$ $\triangleright v_i$ was the second moment of the step $\widehat{m}_i \leftarrow \frac{m_i}{(1 - \beta_1^i)}$ $\triangleright \beta_1, \beta_2$ were the exponential decay rate coefficients $\widehat{v}_i \leftarrow \frac{v_i}{(1 - \beta_2^i)}$ $\theta_i \leftarrow \theta_{i-1} - \alpha \widehat{m}_i / (\sqrt{\widehat{v}_i} + \epsilon)$ **End while****3.2. Model Training**

This study utilised post-screening maize seedling quality indicator data to train the CNN-LSTM model, employing accuracy, precision, recall, F1 score, and loss as the evaluation metrics for model performance [52].

The accuracy rate served as the primary evaluation metric for the grading model, quantifying the proportion of samples accurately predicted by the model relative to the total number of samples. A higher accuracy rate indicates superior grading performance of the model, calculated using the following formula:

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN}. \quad (19)$$

The accuracy rate quantifies the ratio of accurately anticipated positive samples to the total predicted positive samples and is computed as follows:

$$precision = \frac{TP}{TP + FP}. \quad (20)$$

Recall denotes the ratio of samples anticipated to be positive relative to those that are genuinely positive. The calculations were performed using the following formula:

$$recall = \frac{TP}{TP + FN}. \quad (21)$$

The F1 score is the harmonic mean of precision and recall, which assesses the equilibrium between a model's predicted accuracy and the coverage of positive class instances. This was calculated as follows:

$$F1Score = \frac{2 \times precision \times recall}{precision + recall} \quad (22)$$

In this study, true positive (TP) denotes positive samples identified by the model as belonging to the positive category, false positive (FP) denotes negative samples misclassified by the model as positive, false negative (FN) denotes positive samples incorrectly classified as negative, and true negative (TN) denotes negative samples accurately classified as negative by the model.

Quality indices of 3623 Xianyu 335 seedlings were used in the experiment, covering four different categories: optimal seedlings, suboptimal strong seedlings, medium seedlings, and weak seedlings. The sample data were divided into training and test sets in

a ratio of 3:1. Solo thermal coding was employed to assign labels to the sample items, with the categorisation labels presented in Table 3.

Table 3. Sample coding and number of samples divided into different grades of maize seedling quality.

Grade of Seedling Quality	Training Sets	Test Sets	Encoding Label
I	918	305	[1,0,0,0]
II	864	288	[0,1,0,0]
III	702	234	[0,0,1,0]
IV	234	78	[0,0,0,1]
Total	2718	905	--

Note: I is the optimal strong seedling, II is the strong seedling, III is the medium seedling, and IV is the weak seedling.

This study is based on the TensorFlow machine learning framework, built using the Python computer language. The experiment was conducted on a Windows 10 64-bit operating system with an NVIDIA GeForce GTX 1050 Ti (4096 MB); the software environment included Anaconda3 (64-bit), CUDEV10, Python 3.7.15, Tensorflow 2.9.2.

The training set samples were input into the CNN–LSTM model, and network parameters were optimised using the optimiser listed in Algorithm 1. The iteration number (epoch) was set to 100, with a batch size of 64, convolutional kernel sizes were 6 and 4, and the LSTM sizes were 256 and 128. The training accuracy attained its peak, the loss was minimised, and the model exhibited optimal performance. To further evaluate the training effects of the three models, the accuracy versus loss value transformation curves of the training sets of the three models were analysed, as shown in Figure 4.

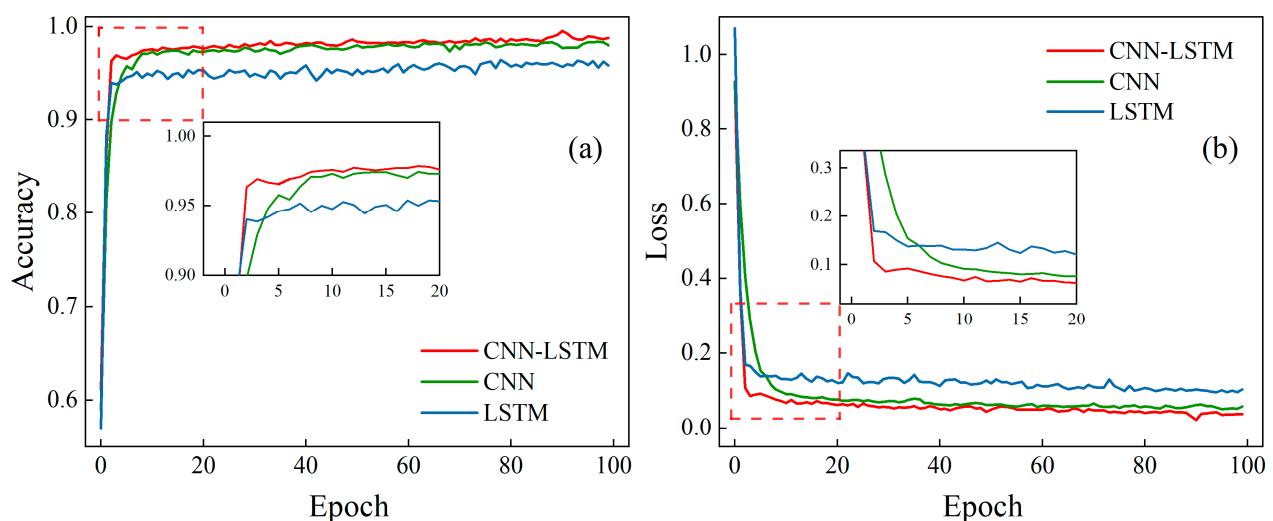


Figure 4. Variation curves of accuracy and loss values for the training set of the three models. (a): Accuracy variation curve. (b): Loss value variation curve.

Figure 4a shows that the red curve (CNN–LSTM accuracy) rises rapidly at the beginning of training and quickly reaches a high accuracy rate, whereas the green curve (CNN accuracy) and the blue curve (LSTM accuracy) converge at a slightly slower rate and eventually reach a lower accuracy level, indicating that the CNN–LSTM model can learn the data features quickly and maintain better performance throughout the training process. The accuracy transformation range for the CNN model training set is 0.5898–0.9838, 0.5691–0.9643 for the LSTM model, and 0.6108–0.9951 for the CNN–LSTM model, with a peak accuracy of 99.51% achieved after 84 training iterations. The accuracy change curves of the training set indicate that the CNN–LSTM model outperformed both the CNN and

LSTM models, exhibiting the most rapid convergence. As shown in Figure 4b, the red curve (CNN–LSTM loss) decreases rapidly at the beginning of the training period, quickly reaches a low loss value, and remains relatively stable in the subsequent training rounds, whereas the green curve (CNN loss) and the blue curve (LSTM loss) decrease slower at the beginning of the training period and reach a relatively high loss value in the end. Thus, the CNN–LSTM model is more capable of learning and fitting to the data than the CNN and LSTM models. The training set loss function curve transformations ranged from 0.0517 to 0.9289 for the CNN model, 0.0960 to 1.0701 for the LSTM model, and 0.0226 to 0.9254 for the CNN–LSTM model. The loss value change curves for the three models demonstrate that the CNN–LSTM model exhibits lower loss values than the CNN and LSTM models. Thus, the proposed method, which integrates the selected maize seedling phenotypic indices with the CNN–LSTM model, effectively identified the quality grade of the maize seedlings.

3.3. Model Simulation Testing

This study employed a one-dimensional CNN and an LSTM to develop a quality-grading model for maize seedlings, and 27 seedling quality indices were collected. A comprehensive evaluation index of the quality of maize seedlings was calculated using the RAGA-PPC model, based on which the individual maize seedling quality index and the comprehensive evaluation index were correlated and analysed, and several representative quality indices were screened. The seven individual quality indicators derived from screening were input into the trained model to assess their performance. The methodology for developing the maize seedling quality-grading model is outlined as Figure 5.

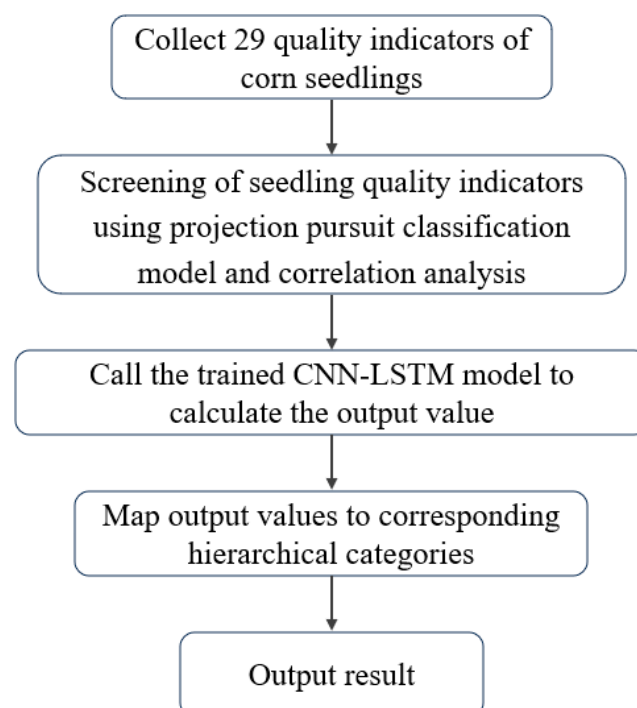


Figure 5. Testing process of maize seedling quality-grading model.

To enhance the assessment of the grading efficacy of the proposed CNN–LSTM neural network, both CNN and LSTM networks were employed independently to evaluate seedling quality. As shown in Figure 6, the recognition accuracies of the proposed CNN–LSTM network model surpassed those of the two individual grading models for both the training and test sets.

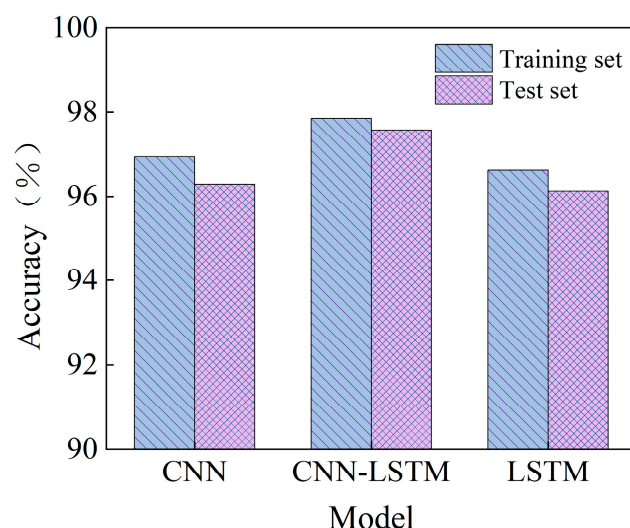


Figure 6. Accuracy of different model prediction sets.

To assess the predictive efficacy of each model intuitively, we compared the prediction outcomes of the CNN and LSTM networks with those of the CNN–LSTM network model developed in this study. Table 4 presents the prediction results for the three models.

Table 4. Prediction results of the three models.

Model	Training Set				Test Set			
	Accuracy	Percentage Increase	Loss	Percentage Reduction	Accuracy	Percentage Increase	Loss	Percentage Reduction
CNN	96.93%	0.95%	0.0909	34.67%	96.29%	1.33%	0.0908	5.70%
LSTM	96.62%	1.27%	0.1106	63.85%	96.13%	1.50%	0.1312	52.74%
CNN–LSTM	97.85%	—	0.0675	—	97.57%	—	0.0859	—

Note: Percentage increase is the percentage increase in accuracy of the CNN–LSTM model compared to the CNN or LSTM model, while percentage decrease is the percentage decrease in loss value of the CNN–LSTM model compared to the CNN or LSTM model.

Table 4 shows that the accuracies of the CNN–LSTM model for the training and test sets were 97.85% and 97.57%, respectively, surpassing the classic CNN model by 0.92% and 1.28% and the LSTM model by 1.23% and 1.44%, respectively. Concurrently, the loss values for the CNN–LSTM network were 0.0675 and 0.0859 for the training and test sets, respectively, reflecting reductions of 0.0234 and 0.0049 compared to the CNN model and 0.0431 and 0.0453 compared to the LSTM model. The CNN–LSTM model exhibited superior recognition accuracy relative to the individual models, indicating that the proposed CNN–LSTM neural network could swiftly and precisely assess the quality of maize seedlings after low-temperature stress. It outperformed both stand-alone CNN and LSTM models and has been established as an effective recognition method. This advancement offers a novel reference and technical guidance for research focused on developing quality-grading models for cold-field maize seedlings using composite neural networks.

Table 5 presents the performance assessment of the maize seedling quality-grading methodology. In Table 5, the highest precision of the CNN–LSTM model is 99.2% for the training set and 98.8% for the test set, and the lowest precision is 95.8% for both the training set and the test machine. The maximum recall rates were 100.0% for the training set and 99.1% for the test set, whereas the lowest recall rate was 94.4%. The mean F1 score for the model training set was 97.78%, whereas that for the test set was 97.20%. The disparities between the highest and lowest precision, recall, and F1 score for the CNN–

LSTM model training set were 3.4%, 5.6%, and 2.7%, respectively, indicating commendable model performance.

Table 5. Performance evaluation of corn seedling quality-grading model.

Evaluation Seedling Grade	Training Set			Test Set		
	Precision	Recall	F1 Score	Precision	Recall	F1 Score
Optimal seedling	99.2%	99.2%	99.2%	98.3%	99.1%	98.7%
Suboptimal seedling	98.8%	94.4%	96.5%	98.8%	94.4%	96.5%
Medium seedling	95.8%	98.9%	97.3%	95.8%	98.9%	97.3%
Weak seedling	96.3%	100.0%	98.1%	96.3%	96.3%	96.3%

The confusion matrix is a widely used visualisation tool for supervised learning algorithms that illustrates the correlation between the number of genuine samples and the number of predicted samples in a classification problem. This study generated a confusion matrix for the test set data to assess the predictive efficacy of the CNN, LSTM, and CNN–LSTM models. Figure 7 shows the confusion matrices of the three models. The vertical and horizontal axes denote the actual and projected sample labels, respectively, and the diagonal line shows the accuracy of sample recognition.

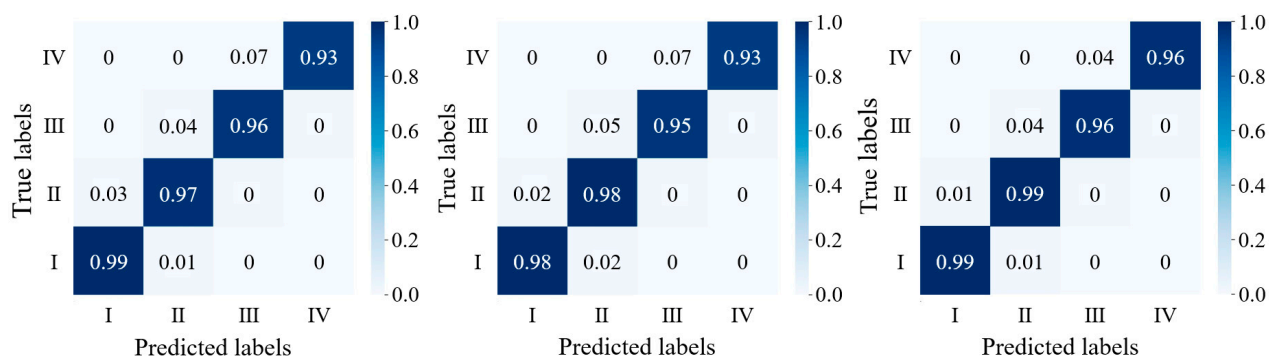


Figure 7. Confusion matrix of three models.

As shown in Figure 7, in classifying optimal seedlings, the CNN–LSTM model has only 0.01 recognition errors, which is 0.01 lower than the LSTM model. In classifying suboptimal seedlings, 0.99 suboptimal seedlings are correctly recognised in the CNN–LSTM model, which is 0.02 and 0.01 higher than the CNN and LSTM models, respectively. In the medium seedling classification, 0.04 medium seedlings were identified as suboptimal seedlings in the CNN–LSTM model, which is 0.01 lower than the LSTM. In the weak seedling classification, 0.04 weak seedlings were identified as medium seedlings in the CNN–LSTM model, which is 0.03 lower than the CNN and LSTM model. This identification confusion may arise from errors in the manual collection of seedling quality indicators or may be caused by individual seedling characteristics. The results of the confusion matrix in Figure 7 show that the sample recognition correctness of the proposed composite CNN–LSTM network is better than those of the single CNN and LSTM models. It is a highly efficient recognition method that provides theoretical references and technical guidance for constructing a quality-grading model for cold-field maize seedlings using DL methods.

4. Discussion

4.1. Model Performance Evaluation

The integration of phenotypic quality markers with advanced DL techniques significantly improved the accuracy of maize seedling grading. Compared to the studies by Wang et al. [53], Li et al. [54], and others, this study reduced the number of maize seedling

quality evaluation indices from 15 to 7 by optimising the screening method and simplifying seedling quality indicator collection, thus improving its operability. The proposed CNN–LSTM cascade model demonstrated 97.57% accuracy, which is 1.61% higher than that of the Inception-v3_GAP model used by Haque et al. [55], primarily owing to the inclusion of indices that comprehensively reflect maize seedling growth. By leveraging CNN’s feature extraction capability and LSTM’s long-term dependency learning, the model overcame the limitations of traditional networks. Compared to the ResNet18 model proposed by Wang et al. [53], the precision, recall, and F1 score of this model improved by 8.76%, 7.28%, and 7.98%.

4.2. Limitations

This study’s reliance on manually collected phenotypic data introduced potential biases. The classification confusion observed was -0.01 for the optimal and suboptimal seedling classes and 0.04 for the medium and weak classes. This study depends on manual data collection, which may generate human subjective measurement bias during the measurement of seedling phenotypic indices. Additionally, there may be idiosyncratic differences between different individual maize seedlings, while the presence of singular samples may also affect the consistency of seedling phenotypic parameters, leading to the emergence of confusion in the identification of samples. The presence of outliers further impacted parameter consistency, potentially affecting sample identification. To mitigate issues in data collection, future research should prioritise automated, precision-based measurement techniques. Consistent sampling techniques and enhanced algorithmic refinements, such as overfitting prevention mechanisms, should be introduced to improve model reliability and robustness.

4.3. Future Research Directions

This study employed seedling phenotypic indices and a CNN–LSTM network to develop a seedling quality-grading model for maize seedlings subjected to low-temperature stress. Seedling quality indices were obtained by measuring and collecting maize seedlings subjected to low-temperature stress, which were further input into the CNN–LSTM network for seedling quality grading. This method is applicable to maize seedling grading and can be extended to various crops. It can also be used to grade the quality of crops subjected to drought, salinity, high temperatures, and other stresses. The proposed composite CNN–LSTM model has strong robustness, high model accuracy, and good model performance. It also presents a new idea and method reference for rapidly and accurately assessing maize seedling quality. Future endeavours will develop portable, field-applicable versions of this model that will enable real-time, large-scale deployment, offering agricultural workers efficient tools for crop quality assessment.

5. Conclusions

The projection-seeking model was used for efficient extraction of maize seedling quality indicators. Seven representative seedling quality indicators were selected, plant height (x_1), stem diameter (x_2), third leaf width (x_{11}), total leaf area (x_{12}), root volume (x_{17}), shoot fresh weight (x_{22}), and root fresh weight (x_{23}), which reflect the coordinated relationships between aboveground and belowground growth.

These indices were used to construct a CNN–LSTM-based grading model for maize seedlings. The model achieved an accuracy of 97.57%, surpassing traditional CNN and LSTM models by 1.28% and 1.44%, respectively. Furthermore, the model’s loss value of 0.0859 was notably lower than that of stand-alone CNN and LSTM models, indicating its superior precision and stability. This high-performing grading model facilitates rapid

and precise evaluation of maize seedling quality, offering a robust theoretical basis and technical support for enhancing maize production management, especially under cold stress conditions.

This study contributes to the mechanisation and standardisation of maize production, promotes better disaster mitigation strategies, and equips agricultural systems to address the challenges of climate change effectively. Future work will build on the findings of this study to identify suitable hardware for integrating the algorithm into portable mobile devices. This will enable its application and promotion in field production practices, helping agricultural workers to accurately and conveniently evaluate the grading of crop seedlings.

Author Contributions: Conceptualisation, methodology, software, writing—original draft, writing—review and editing, project administration, S.Y. (Song Yu); investigation, writing—original draft, software, data curation, visualisation, Y.L. (Yuxin Lu); investigation, validation, formal analysis, software, Y.Z. (Yutao Zhang); investigation, validation, formal analysis, software, X.L.; conceptualisation, software, data curation, writing—review and editing, funding acquisition, supervision, Y.Z. (Yifei Zhang); investigation, validation, formal analysis, M.L.; investigation, validation, formal analysis, H.D.; investigation, validation, formal analysis, S.S.; investigation, validation, formal analysis, J.L.; investigation, validation, formal analysis, S.Y. (Shiqiang Yu); methodology, software, formal analysis, J.Y.; methodology, software, formal analysis, H.G.; methodology, resources, Y.L. (Yanjie Lv); methodology, visualisation, C.Z. All authors have read and agreed to the published version of the manuscript.

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