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DEEP LEARNING-BASED DETECTION OF VERNACULAR HERITAGE HOUSES IN SUMBA ISLAND USING BSTO-VGG16-ALNN AND BIG DATA ANALYTICS

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ABSTRACT

In the conventional settlements of Sumba Island, the nearby local area progressively changes design to meet their consistently moving necessities. The social legacy, exemplified in vernacular houses, holds extensive interest for the travel industry. By grasping and advancing the social meaning of these houses, we can add to manageable the travel industry improvement, supporting the neighborhood economy and encouraging consciousness of the social lavishness of the district. As we dig into the examination of the social legacy inside vernacular houses, it becomes evident that these designs wrestle with difficulties like rot, underlying weaknesses, and natural tensions. Despite this, the ever-changing technological landscape presents promising opportunities for the preservation of these priceless cultural assets. The incorporation of progressively complex PC vision innovation, joined with the openness of high-goal remote detecting pictures, presents an extraordinary way to deal with exactly assess and quantify the many-sided subtleties of Earth's regular and fake conditions for enormous scope. In this undertaking, our work proposes a strategy using profound learning methods and huge information examination for distinguishing the social legacy of vernacular houses in Sumba Island, Indonesia. At first, we utilize the boosted sooty tern optimization (BSTO) calculation for target division, really isolating vernacular houses from the grave remote detecting pictures. Subsequently, we present the pre-prepared VGG-16 engineering to extricate highlights from the fragmented objective picture. Also, we carry out the adaptive learning neural network (ALNN) for the exact programmed discovery of vernacular houses. Utilizing Sumba Island tiles, we validate the efficacy of our BSTO-VGG16-ALNN method and demonstrate impressive results.

I. INTRODUCTION

We are living in the "Age of Data", with new information being delivered from all businesses and public bodies at an exceptional, and continually developing rate thus, there has been an extraordinary promotion which has driven associations to make significant interests in their mission to investigate how they can utilize their information to make esteem [1]. The primary reason enormous information examination expands on is that by dissecting huge volumes of unstructured information from various sources, noteworthy experiences can be produced that can assist firms with changing their business and gain an edge over their opposition [2]. Having the option to get such information produced knowledge are especially important, particularly for associations that work in powerful and high-paced business conditions, where pursuing informed choices is basic.

Regardless of much commitment from enormous information examination [3] there has been fundamentally less exploration on how associations should be organized to create business esteem from such ventures, and a restricted comprehension on the transaction of variables that drive execution gains [4]. Most reports to date on the worth of huge information examination come from consultancy firms, well known press, and disconnected contextual investigations, which neglect to expand on exact outcomes from enormous scope investigations and need hypothetical knowledge. Moreover, [5] late investigations have noticed that there is as yet a sizeable number of organizations that neglect to catch esteem from their huge information speculations and, surprisingly, some that contend that large information might sting instead of help organizations [6]. Accordingly, there is deficient comprehension about how associations ought to move toward their large information drives, and scant observational help to direct esteem creation from such speculations [7]. Bigdata, with their capability to find out esteemed bits of knowledge for improved dynamic cycle, have as of late drawn in significant interest from the two scholastics and experts. In order to extract useful information from big data, numerous businesses are adopting big data analytics, which is increasingly becoming a popular method [8].

The investigation cycle, including the sending and utilization of enormous information examination devices, is considered by associations to be an instrument to work on functional proficiency however it has key potential, drive new income streams and gain upper hands over business rivals. Be that as it may, there are various sorts of insightful applications to consider [9]. Consequently, preceding rushed use and purchasing expensive bigdata instruments, there is a requirement for associations to initially comprehend the enormous information examination scene. Given the critical idea of the BD and huge information examination, this paper presents a cutting edge survey that presents an all encompassing perspective on the bigdata challenges and large information investigation strategies utilized by associations to help other people comprehend this scene with the target of pursuing strong venture choices [10]. To explore in such an unstable, mind boggling and questionable climate, coordinate apparent development capacity is acknowledged as a urgent capability [11]. Advancement alludes to foster worth to meet clients' necessities and market needs. Also, information driven development depends on making esteem by utilizing information and advanced apparatuses [12]. The speed of development is changing quickly as per mechanical upgrades and the reception of advancement is profoundly reliant upon the information the board [13]. The noticeable upper hand is gotten from capacity to utilize significant apparatuses to make important data. Businesses use big data, in particular, a lot to come up with new ideas, processes, and markets [14]. To centers around computerized devices, large information examination and man-made reasoning and their effect on development. The problematic impacts of information driven advancement in the business world are examined [15].

It is viewed as that this section might empower chiefs to make experiences and to more readily comprehend information driven development. The attracts consideration is utilized to the limit of AI frameworks to learn and change over the long run, progressively laying out their own sub-objectives, and their capacity to adjust to nearby circumstances by means of outer sensor data or refreshed input information [16]. Human originators of these frameworks choose and set their underlying boundaries and the all-encompassing objective which these frameworks are expected to streamline [17]. Simultaneously, AI frameworks are intended to work by settling on free choices that pick between options in manners that are not pre-modified in that frame of mind, to do as such with practically no human mediation [18]. Since these frameworks advance powerfully and iteratively from their current circumstance, which is it frequently unstable and constantly changing, this has suggestions for the soundness and consistency of their activity [19]. Specifically, these frameworks can possibly advance unexpectedly. In this time of computerized information overflow, moral difficulties have arisen as a squeezing concern. Data analytics' complex ethical challenges, including privacy invasion, algorithm bias, and security risks, are the focus of this topic [20]. We hope to shed light on the ethical quandaries and provide insights into how society can navigate this data-driven landscape responsibly and ethically by examining real-world case studies and proposing solutions.

Our contributions. The proposed profound learning procedure with huge information examination for social legacy recognition in vernacular houses on Sumba Island, Indonesia, is intended to give an extensive and exact strategy to recognizing these social resources. The significant commitments of this strategy are framed beneath:

1. The underlying step includes the utilization of the boosted sooty tern optimization (BSTO) calculation for target division. BSTO improvement upgrades the accuracy of division, guaranteeing that the calculation detaches the objective designs precisely in the midst of the assorted data present in the pictures.
2. Following objective division, the VGG-16 pre-prepared engineering is used for highlight extraction from the fragmented objective picture. VGG-16 is a convolutional neural network (CNN) known for its viability in picture acknowledgment errands.
3. The proposed strategy integrates a hybrid adaptive learning neural network (ALNN) for the programmed discovery of vernacular houses. This brain network is utilized to adjust and gain from the highlights separated by VGG-16, upgrading the exactness of the identification cycle.
4. To survey and approve the presentation of the BSTO-VGG16-ALNN strategy, the procedure is applied to Sumba Island tiles. It includes utilizing the model to examine genuine information from the district, affirming its viability in precisely identify vernacular houses.

The rest of this paper is organized as follows. Section 2 gives the review of recent works related to the big data analytics for cultural heritage detection. Section 3 provides the detailed working process of our BSTO-ALNN technique for economy forecasting with the detailed mathematical models. The results and comparative analysis of models for the big data analytics for cultural heritage detection is discussed in the Section 4. Finally, the paper concludes in Section 5.

II. RELATED WORKS

II.1 STATE-OF-ART STUDIES

DAS et al. [21] have asserted that big data is just beginning to transform healthcare and propel the sector forward on numerous fronts. The progressions in medication, advancement, and funding that large information in medical care ensures offer plans that gain ground in understanding the consideration and drive esteem in medical services associations. With the instrument's advancement, methods that utilize THz waves for pharmaceutical applications are rapidly evolving. THz imaging can possibly be used in assessing a couple of designs. The responsibility of this examination is to make recommendations for the THz imaging strategy and information examination, preferably having an effect in carrying it closer to being clinically important development. Jindal et al. [22] have proposed a tensor-based method for managing big data to reduce the dimensionality of IoE environment data in a smart city. This center information is then put away on the cloud in the decreased structure. Subsequent to decreasing dimensionality of information, it tends to be utilized for offering many types of assistance in savvy urban areas and its application to give request reaction administrations is talked about in this paper. The support vector machine (SVM) based classifier is utilized to characterize the end-clients into ordinary, over-burden and under stacked classifications from the center information. When such clients are recognized to partake popular reaction system, utilities can devise specific answers for handle their interest reaction to change their heap prerequisites so the general burden in the brilliant city is ideally made due.

Silva et al. [23] have proposed a bigdata examination installed brilliant city design, which is additionally coordinated with the web by means of a shrewd door. Incorporation with the web 14 gives a general correspondence stage to beat the stage incongruencies of savvy things. They assessed credible informational indexes to decide the limit values for canny navigation and to introduce the exhibition improvement acquired in information handling. At last, 17 introduced an illustrative state move with the trap of things coordinated brilliant structure design to uncover the exhibition enhancements of the shrewd city engineering regarding network execution and energy the board of savvy structures. Ordonez et al. [24] have proposed an exploration point, including not having a data set model, inventive capacity past columns and scale out equal handling. Numerous presumptions in view of a concentrated information distribution center or unbending data set have been debilitated and, surprisingly, vanished. Most would agree enormous information examination has left information warehousing and information mining research behind. Before designing extended data warehouse and analytics applications in the bigdata era, they hope that readers will find the content of this special issue interesting and will be inspired to investigate the challenges that remain. Fernández et al. [25] have proposed a free and open-source method for automatically configuring and deploying a Spark cluster.

It has been created with a user-friendly graphical user interface to make managing Spark clusters simple and effective, automate cluster deployment, and quickly start up Hadoop's distributed file system. In addition, LadonSpark offers the capacity to incorporate any algorithm into the system. That is, the client just has to give the executable record and the quantity of required inputs for appropriate definition. Also, bunching, relapse, characterization, and affiliation rules calculations are as of now coordinated with the goal that clients can test its ease of use from its underlying establishment. Kabugo et al. [26] have proposed an interaction information examination stage worked around the idea of industry 4.0. Big-data software tools, ML algorithms, and cutting-edge IIoT platforms are all incorporated into the platform. The stage accentuates the utilization of ML strategies for process information examination while utilizing enormous information handling devices and exploiting the presently accessible modern grade distributed computing stages. The modern materialness of the stage was exhibited by the improvement of delicate sensors for use in a waste-to-energy plant. For the situation study, the work concentrated on information driven delicate sensors to anticipate syngas warming worth and hot vent gas temperature. The displaying results showed that, in situations where process information about the cycle peculiarities within reach is restricted, information driven delicate sensors are valuable devices for prescient information examination.

Fang et al. [27] have proposed a cyber-physical production system (CPPS) utilizing information investigation is proposed to empower creation perceivability. It utilizes information stream handling ways to deal with clean excess information effectively. Bayesian derivation motor is prepared by Ming the authentic information disconnected, is utilized to recognize the exactness of a RFID-caught occasion on the web. Then, at that point, complex occasion handling is applied to combine multi-source heterogeneous information. The creation progress perceivability is accomplished by the business cycle the board. The system shows how important it is to implement real-time data collection, processing, and visibility in order to increase production efficiency. Zhao et al. [28] have proposed a basic job in information mining, and has gotten extraordinary accomplishment to tackle application issues, local area examination, picture recovery, customized proposal, movement forecast, and so forth. Albeit the current strategies have predominant execution on some little or certain datasets, they miss the mark while bunching is performed on CPSS enormous information as a result of the significant expense of calculation and capacity. With the strong distributed computing, this challenge can be really tended to, however it carries colossal danger to individual or organization's security. In academia, privacy-preserving data mining has received a lot of attention.

Northcott et al. [29] have discussed the ascent of information serious science, or huge information, altered our capacity to anticipate. It suggests need for expectation over causal comprehension, and decreased job for hypothesis and human specialists. They look at four significant situations where expectation is alluring: political elections, the weather, GDP, and the outcomes of economic experiment-suggested interventions. The methodology embraced is especially important in managing such a complicated and touchy issue, as it considers the environment of finding out about the subject across different settings and media assets. Bilal et al. [30] have proposed a benchmarking framework for delicate assessment utilizing Huge Information of 1.2 terabytes, including 5.7 million cells. An all encompassing rundown of seventeen KPIs is distinguished from the email information utilizing Text Mining draws near. The idea of a deep ensemble learner based on the decomposition-integration method is at the heart of this work. In the deterioration stage, the model predicts a few property explicit benchmarks for each KPI utilizing setting mindful calculation. The profound brain network-based students are prepared to create last venture delicate KPI benchmark.

In the spring, the learner will be used as a tool to help evaluate power infrastructure projects for tenders. A delicate of 60km underground cabling project is assessed utilizing the student. The tender's key performance indicators (KPIs) were automatically identified by the system as requiring additional attention to improve profitability performance.

II.2 RESEARCH GAPS

The identification of built cultural heritage marks fundamental stage in preserving our collective human legacy. Its significance spans a myriad of purposes, encompassing preservation, tourism, education, identity, and fostering international collaboration. Acknowledging the importance of cultural heritage significantly contributes to the enrichment of societies and a deeper appreciation of diverse global history. In a study conducted by Monna et al. [31], they introduced a replicable workflow designed for the automatic detection of buildings from satellite imagery. This research demonstrated the efficiency of modern computer vision techniques, specifically those rooted in deep learning, in accomplishing a task that would be exceptionally time-consuming if undertaken manually. The review thought about eight profound learning designs in view of convolutional brain organizations, assessing their ability to recognize and find conventional houses from satellite pictures exactly. Particularly successful was the combination of artificial data augmentation and the Faster R-CNN ResNet 101 architecture. The R-CNN ResNet 101 architecture prepared with 1033 examples of vernacular houses, displayed its capability in computerizing the ID cycle, introducing a promising road for the use of cutting-edge innovations in social legacy recognition [32]. Distinguishing assembled social legacy through the utilization of profound learning strategies with enormous information investigation presents multi-layered scene full of difficulties [21], [22].

Algorithms that are capable of accurately identifying various building types are needed to overcome the significant obstacle posed by the architectural diversity inherent in cultural heritage structures. Furthermore, factor conditions in satellite symbolism, like changes in lighting, weather patterns, and goal, add to the intricacy of the location task [23]. The most common way of clarifying and naming enormous datasets for the purpose of preparing can be work escalated; requiring master information, particularly while managing assorted building highlights. Additionally, the creation of robust and generalized models is hampered by the lack of labeled training data for particular cultural heritage sites [24]. In metropolitan conditions, firmly arranged structures and visual mess can prompt covering structures, confusing exact recognition. Additionally, the scale abberations among structures inside social legacy destinations present difficulties for discovery models in adjusting to shifting sizes. To address these difficulties, the incorporation of profound learning methods with enormous information investigation arises as a promising arrangement [25]. Profound learning calculations succeed in mechanized highlight extraction, permitting them to observe multifaceted compositional subtleties from enormous datasets. Large information examination further work with information expansion, enhancing preparing datasets and working on model power against varieties in lighting, points, and conditions [26].

Besides, the arrangement of cutting edge structures demonstrates viable in catching spatial ordered progressions and mind boggling subtleties in satellite symbolism, consequently improving the exactness of assembled legacy identification. Nonetheless, in spite of these progressions, potential issues might emerge after execution [27]. Overfitting is concern, where a model turns out to be excessively intended for the preparation information lead to decreased speculation on new and concealed social legacy pictures [28]. Calculation predisposition is another thought, as models might exhibit inclinations in view of the creation of the preparation information, bringing about errors or misclassifications for specific kinds of social legacy structures. The interpretability and logic of profound learning models present difficulties, making it hard to comprehend the thinking behind unambiguous identification [29]. Also, moral contemplations, for example, issues connected with protection, information possession, and social responsiveness, warrant cautious consideration [30]. Tending to these difficulties and potential issues requires fastidious model turn of events, careful approval, and progressing observing. To address the difficulties and potential issues recognized with regards to distinguishing constructed social legacy utilizing profound learning methods with enormous information examination.

1. Foster profound learning models that can actually deal with different engineering styles present in constructed social legacy, guaranteeing hearty execution across different designs.
2. Investigate effective approaches to data annotation and labeling in order to speed up the process of creating massive labeled datasets and guarantee that expert knowledge is effectively utilized for various architectural features.
3. Upgrade robotized highlight extraction capacities in profound learning models, guaranteeing that these models can successfully catch and break down complicated highlights from enormous datasets.
4. Ensure that deep learning models do not become overly specific to the training data and maintain generalization on new and unseen cultural heritage images by developing strategies to mitigate over fitting challenges.

III. PROPOSED METHODOLOGY

The proposed procedure for recognizing the social legacy of vernacular houses in Sumba Island, Indonesia, unfurls through a deliberate cycle delineated in Fig. 1. Beginning with input remote detecting pictures catching the geographic district of interest, the framework goes through a critical period of picture preprocessing. This underlying step guarantees ideal picture quality by utilizing methods like sound decrease, contrast upgrade, and standardization. In this manner, the boosted sooty tern optimization (BSTO) calculation becomes possibly the most important factor for the division of vernacular houses. This enhancement calculation is fastidiously intended for target division, really separating areas inside the info remote detecting pictures that relate to vernacular houses. When the division is finished, the framework extricates the designated vernacular house regions from the preprocessed remote detecting pictures. This particular extraction confines locales of interest, which are characteristic of potential social legacy structures. Pushing ahead, the element extraction process is started utilizing the VGG-16 engineering, a prestigious profound convolutional neural network (CNN) commended for its viability in picture related undertakings.

This stage includes the extraction of more profound elements, enveloping surface, semantic, and factual highlights, from the portioned vernacular house regions. These removed elements structure a far reaching portrayal of the multifaceted qualities related with social legacy structures. The last and basic step involves the programmed identification of constructed social legacy utilizing a hybrid adaptive learning neural network (ALNN) strategy.

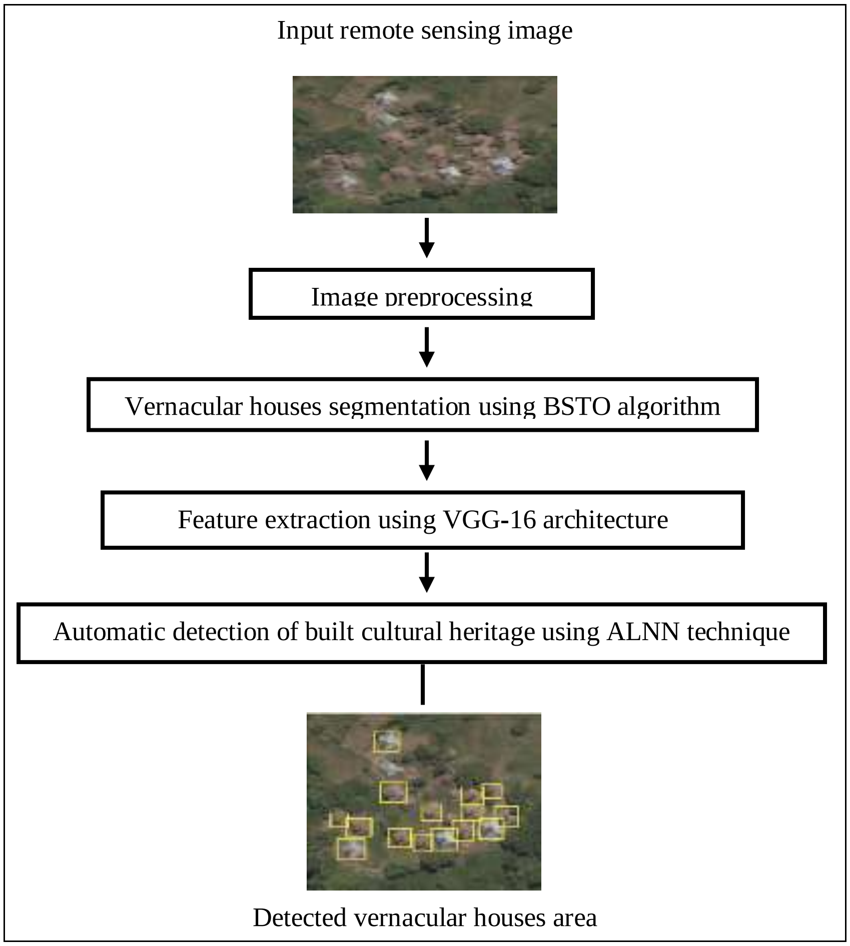

Figure 1: Framework plan of proposed procedure for identify the social legacy of vernacular houses in Sumba Island, Indonesia.
Source: Authors, (2026).

This ALNN is intricately designed to adapt to and learn from the VGG-16 architecture's extracted features. The cross breed nature of the ALNN consolidates different learning methodologies, upgrading its ability to precisely identify and group social legacy structures. The results of this framework configuration give important data about the presence and circulation of vernacular houses on Sumba Island, contributing altogether to continuous social legacy conservation tries. The goal of the proposed method is to provide a comprehensive and precise solution for identifying cultural heritage structures in the unique context of Sumba Island, Indonesia, by integrating advanced optimization algorithms, deep learning, and adaptive learning techniques.

III.1 TARGET SEGMENTATION

In the underlying period of the social legacy identification process, target division assumes a urgent part, and to achieve this, the boosted sooty tern optimization (BSTO) calculation is utilized. The BSTO calculation draws motivation from the rummaging conduct of dingy terns, seabirds known for their proficient hunting procedures. Its essential objective inside this application is to advance the division of vernacular houses inside remote detecting pictures. The calculation starts by introducing a populace of likely arrangements, regarding them as individual specialists similar to rummaging birds. Through a series of optimization iterations, these solutions, which represent potential regions for vernacular houses, undergo iterative refinement. During the iterative process, the solutions are modified in accordance with rules that are derived from the foraging behavior of sooty terns. The goal is to maximize a specified goodness function that represents the accuracy of the segmentation. Critically, the BSTO calculation displays versatile attributes, powerfully changing its boundaries in light of the advancement of improvement and gaining from the investigation of the arrangement space. A definitive result is the successful partition of vernacular houses from the encompassing setting in the remote detecting pictures. BSTO calculation's proficiency lies in its capacity to deal with complex objective division errands, exhibiting its flexibility and improvement ability in precisely recognizing social legacy structures inside assorted and dynamic scenes caught in the pictures. Seabirds called sooties, or Onychophyrionfuscatus, can be found all over the world. There are numerous sizes and masses of sooty bush varieties.

Dingy birds are seabirds tracked down all around the world and come in various assortments of various loads and sizes. They feed on fish, bugs, creatures of land and water, worms and reptiles. They typically live in states and utilize their knowledge to find and go after prey. BSTO calculation starts by introducing potential arrangements addressing up-and-comer districts for vernacular houses in remote detecting pictures. It utilizes a goal capability to assess arrangement quality, with a helping component supporting fruitful techniques. Through iterative advancement and versatile learning, the calculation progressively changes its boundaries to upgrade precision. A union check decides when to end emphasess, giving last division result that precisely recognizes vernacular houses. The adaptive nature and boosting mechanism of the BSTO algorithm make it ideal for target segmentation tasks in cultural heritage detection. Relocation and hunting are a significant part of the way of behaving of dingy pigs, and relocation is characterized as the occasional development of these birds starting with one spot then onto the next looking for energy-giving food. By moving, Alcoholic should keep away from the contention depicted beneath.

$$\vec{C}_{ts} = T_B \times \vec{Q}_{ts}(z) \tag{1}$$

$$T_B = c_F - (Z \times (c_F / Iter_{\max}) \tag{2}$$

The condition of an ash stem that has not slammed into another ash is the condition of the momentum sediment stem, Z is the ebb and flow cycle, and TB is a control variable to change ash movement and TB in a specific pursuit district. Subsequent to staying away from crashes, the smell converges with its best neighbors as per the accompanying recipe.

$$\vec{m}_{ts} = c_b \times (\vec{Q}_{ats}(z) - \vec{Q}_{ts}(Z)) \tag{3}$$

$$c_A = 0.5 \times r_{and} \tag{4}$$

To address various places of the sediment bramble, ideal ash is an irregular variable and r is an irregular number in the reach [0,1]. Dingy turn status can be refreshed as follows

$$\vec{d}_{ts} = \vec{C}_{ts} + \vec{m}_{ts} \tag{5}$$

It's $\vec{d}_{ts}$ difference between smell and great soot. Ash tufts foster a twisting conduct in the breeze, which is characterized as follows

$$y' = r_{adi} \times \sin(j) \tag{6}$$

$$x' = r_{adi} \times \cos(j) \tag{7}$$

$$Z' = r_{adi} \times j \tag{8}$$

$$R = U \times E^{KV} \tag{9}$$

Where demonstrates the span of each helical turn, I is the variable in range [$0 \le K \le 2\pi$], u and v characterize the helical shape steady, e is a characteristic logarithm. The following changes can be made to the sooty tern's position:

$$\vec{Q}_{ts}(z) = \vec{d}_{ts} \times (y' + x' + z') \times \vec{Q}_{ats}(z) \tag{10}$$

where $\vec{Q}_{ts}(z)$ informs the locations of other sooty terns and custody the best result.

III.2 FEATURE EXTRACTION

Following the target segmentation of vernacular houses within remote sensing images, the subsequent step in the cultural heritage detection process involves feature extraction. This crucial stage is facilitated by the introduction of the pre-trained VGG-16 architecture, a deep convolutional neural network renowned for its hierarchical feature learning capabilities. VGG-16, comprising of 16 layers, goes through move getting the hang of, having been pre-prepared on broad datasets like ImageNet. Move gaining permits the model to use information acquired from these datasets, upgrading its capacity to remove appropriate elements from the divided objective picture. As the picture navigates through the organization, convolutional layers catch both low-level elements, like edges and surfaces, and significant level conceptual highlights illustrative of the vernacular houses. The element extraction process creates itemized highlight maps, exemplifying surface, semantic data, and measurable attributes characteristic for the fragmented objective picture. VGG-16's versatility empowers it to perceive one of a kind building designs related with social legacy structures. The result contains high-layered include vectors, filling in as rich portrayals that encode the unmistakable parts of vernacular houses for ensuing errands, especially programmed identification. The joining of the pre-prepared VGG-16 design in the component extraction stage improves the viability and flexibility of the social legacy identification pipeline. The most common way of using the pre-prepared VGG-16 design includes a few vital stages with regards to highlight extraction for social legacy location from divided target pictures.

- Utilizing move learning, the pre-prepared VGG-16 model is instated with loads and inclinations gained during its pre-preparing on pictures from dataset. This instatement gives the model an abundance of information about broad visual elements, empowering it to adjust to additional particular errands with restricted named information.
- The fragmented objective picture, acquired through the earlier objective division stage, fills in as the contribution to the pre-prepared VGG-16 model. The isolated areas that represent vernacular homes are included in this image.
- The info picture goes through forward spread through the layers of the VGG-16 engineering. Each layer, including convolution and pooling layers, separates various leveled highlights from the portioned target picture.
- The VGG-16 model's various layers produce feature maps. These component maps address the actuations of neurons because of explicit examples and surfaces present in the divided objective picture.
- The architecture of VGG-16 makes it easier to learn features in a hierarchical fashion. The lower layers take in low-level features like edges and textures, while the higher layers take in more abstract and semantic features.
- The flexibility of the pre-prepared VGG-16 model permits it to perceive and catch highlights intended for vernacular houses. The model adjusts its learned portrayals to the design examples and qualities related with social legacy structures.
- The last result of the pre-prepared VGG-16 design is a high-layered include vector. The cultural heritage detection process as a whole is augmented by VGG-16's high-dimensional feature vector output.

III.3 AUTOMATIC DETECTION OF VERNACULAR HOUSES AREA

The hybrid adaptive learning neural network (ALNN) is used to perform the crucial step in the process of identifying cultural heritage, which is the automatic detection of vernacular houses. It specific brain organization, described by its crossover nature, consolidates different learning techniques to improve precision. Based upon a adaptive learning framework ALNN obliges dynamic changes of its boundaries in view of the elements it processes. The brain network engineering, intended to handle high-layered include vectors got from the pre-prepared VGG-16 model, goes through preparing to learn progressive course of vernacular house qualities. The educational experience coordinates different learning methodologies, possibly joining regulated and unaided procedures to further develop speculation. Enhancement procedures guarantee accuracy in recognizing vernacular houses, including tweaking boundaries and utilizing regularization strategies. Rigorous accuracy evaluation using validation datasets ensures the model's reliability in real-world scenarios. The output of ALNN represents the automatic detection of vernacular houses, contributing valuable information for cultural heritage preservation and research within the broader context of remote sensing images. First, we define the parameter initialization of ALNN is define as follows.

$$F_{nn}(X)=W^{T}J(X)+\varepsilon \tag{11}$$

where $X=[X_1, X_2,....,X_m]$ is the input vector, W^e [1, 2,...,l] is the weight vector. The typical Gaussian basis function is compute as follows.

$$G_i(X)=\exp\left[-\frac{(X-\upsilon_i)^t(X-\upsilon_i)}{c_i^2}\right], i=1,...,l \tag{12}$$

where $G_i(X)$ The focuses of the Gaussian capability and the width of the premise are individually addressed by the potential outcomes guess, and the computational speed is affected by the quantity of secret layers. A solitary secret brain network is decided to best inexact the obscure capability.

$$W^{*}=\arg\min\left[\sup\left\|\hat{W}^{R}D(X)-F_{mm}(X)\right\|\right] \tag{13}$$

$$\Omega_W=\left\{\hat{W}\left\|\hat{W}\right\|\leq M\right\} \tag{14}$$

The single vulnerability can be addressed as a component of the estimation execution of the brain network as follows:

$$\alpha(X)=W_a^{*E}G_a(x)+\varepsilon_a^{*} \tag{15}$$

where $\alpha(x)$ is the ideal guess mistake, indicated There is an upper bound on the assessed blunder ̄ε to the degree that |ε∗α| ≤̄ε. The composite unsettling influence is thought to be an estimated hypothesis of nonpartisan organizations that permits us to establish that the pace of progress fulfills | | | greatest the following is the identification model in light of the system.

$$\begin{cases}\breve{x}_1=\breve{x}_2\\ \breve{x}_2=-\alpha_F\zeta+\hat{\alpha}(x)+gu\end{cases} \tag{16}$$

Where the identification model's state variable vector is denoted by $\breve{x}_1 = [\breve{x}_1, \breve{x}_2]$. The channel displaying mistake is characterized as follows.

$$\zeta = \breve{x}_1 - \breve{x}_2 \tag{17}$$

Subbing into one can acquire the accompanying unique condition.

$$\breve{x}_2 = G_1(s)\left(\alpha_F x_2 + \hat{\alpha}(x) + gu\right) \tag{18}$$

where D_1 (s) is equal to 1. The low-pass filter can be used to reduce the noise signal produced during system output measurement if the appropriate F is selected.

$$\begin{cases} \breve{x}_1 = \breve{x}_2 \\ \breve{x}_2 = -k_F^e \zeta + \hat{\alpha}(\breve{x}) + gu + \hat{D} \end{cases} \tag{19}$$

The recreation mistake vector is determined as follows: where lD = [k_{f_1}, k_{f_2}] T is the addition vector, T is the reproduction blunder vector, x is the sexually transmitted disease state gauge vector, T is the recreation mistake vector, and D is the gauge D.

$$\begin{cases} \zeta_1 = \breve{x}_1 - \vartheta_0 \\ \zeta_2 = \zeta_1 = \breve{x}_2 - \vartheta_1 \end{cases} \tag{20}$$

By substituting, we can get the updated solution as follows.

$$\breve{x}_1 + k_{F_2}\breve{x}_1 + k_{D_1}\breve{x}_1 = \Delta + \breve{\alpha}(\breve{x}_1) + gu + \breve{D} \tag{21}$$

A second-request low-pass channel relates to elements, which is characterized as follows

$$\breve{x}_1 = J_2(s)\left(\nabla + \hat{\alpha}(\breve{x}) + gu + \breve{D}\right) \tag{22}$$

$$D_2(s) = \frac{1}{s^2 + k_{F_1}s + k_{f_2}} \tag{23}$$

The improved identification model is used to reduce noise by selecting the appropriate constants k_{F_1} and k_{F_2}.

$$\zeta = A_F\zeta - B\left(\tilde{Q}_A^T G_A(x) + \tilde{Q}_A^T G_A(\hat{x}) - \tilde{Q}_A^T G_A(\hat{x}) - \tilde{Q}_A^T G_A(\hat{x}) + \tilde{D} + \breve{x}_2\right) \tag{24}$$

The Lyapunov condition exists with the end goal that assuming the genuine underlying foundations of the trademark polynomial AF are on the left half of the complicated plane.

$$A_F^T P_F + P_F A_F + Q_F = 0 \tag{25}$$

The symmetric positive-definite matrices P, F, and Q_F are also called optimal design measure.

$$\hat{W}_A = \begin{cases} -\sigma_1 G_A(\hat{x})\ if\ \left(\|\hat{W}_A\| \le M_A\right) or \\ \left(\|\hat{W}_A\| = M_A G_A^T(\hat{x})\hat{W}_A \ge 0\right) \\ P_A[.] otherwise \end{cases} \tag{26}$$

where is the positive constant ($\hat{W}$) and an illustration of the projection operator $P_A[.]$:

$$P_a[.] = -\sigma_1 G_A(\hat{x}) + \sigma_1 \frac{D_A^T(\hat{x})\hat{W}}{\left\|\hat{W}_a\right\|^2}\hat{W}_a \tag{27}$$

where p is the positive-clear symmetric network and fulfills the accompanying Lyapunov condition

$$A^T P + PA + Q = 0 \tag{28}$$

A non-ear disturbance observer is used to provide a more accurate estimation of the compound disturbance:

$$\upsilon = A + k_s C^e p_F \zeta \tag{29}$$

The estimation of disturbance is formulated as follows.

$$\hat{D} = \hat{\nu} - h_s C^e P_F \zeta \tag{30}$$

Considering the time derivative of ν can be compute as follows.

$$\upsilon = D + h_s C^E P_F \zeta = D + h_s C^E P_F \zeta - k_s C^e P_s P\left(\hat{Q}_a^E g_a(x) + \hat{W}_a^E g_a(\hat{x}) + \hat{W} + \hat{x}_2\right) \tag{31}$$

The time subordinate of ν̂ is built as follows:

$$\hat{\upsilon} = +k_s b^t p_f af \zeta \tag{32}$$

$$\hat{\upsilon} = D - \tilde{D} = \tilde{D} \tag{33}$$

Differentiating the above condition to update the final fitness solution, this defines as follows.

$$\hat{\upsilon} = \upsilon - \hat{\upsilon} = D - P_a\left(\tilde{W}_a^t J_a(z) + \tilde{W}_s^R H_s(\hat{x}) - \tilde{W}_a^t J_a(z) + \tilde{F} + x_2\right) \tag{34}$$

The ALNN's ability to handle complex feature sets and its adaptive learning capabilities make it well-suited for accurately staging the lung cancer based on the diverse information available from the lung tumor images.

IV. RESULTS AND DISCUSSION

Within this section, we showcase the outcomes and conduct a comparative analysis between the proposed methodology and established techniques for detecting the cultural heritage embodied in vernacular houses on Sumba Island, Indonesia. The validation of the BSTO-ALNN technique's performance utilizes remote sensing images collected specifically from Sumba Island. A comparative evaluation is conducted by pitting the results of the BSTO-VGG16-ALNN technique against those of existing methods, choice tree, k-closest neighbor, brain organization, support vector machine relapse (SVR), irregular woods, Ssd_inception_v2, Ssd_resnet_50_fpn, Faster_rcnn_ inception_v2, Faster_rcnn_resnet50 and Faster_rcnn_resnet101 [31]. The different exhibition measurements are utilized to completely survey and compare the efficacy of both the proposed and existing techniques.

IV.1 DATASET DESCRIPTION

The evaluation of both proposed and laid out procedures was directed utilizing Python 3.7 and the TensorFlow article discovery Programming interface, with pre-prepared models obtained from the TensorFlow identification model zoo landing page. The overhang of roofs over walls, especially for rainwater protection, makes it difficult to accurately measure a house's surface area. This can cause variations of up to 25%. Nonetheless, given methodical North-South or East-West directions, bouncing boxes would adjust intimately with rooftops. On account of variable house directions, the rooftop is conceptualized as a square recorded in another square (jumping box), where the rooftop surface reaches from roughly half to 100 percent of the case surface, dependent upon the house's direction. Beginning investigations included preparing up-and-comer models with 480 and 1033 occurrences of conventional houses and an assessment set containing 124 and 363 things, individually, without manufactured information increase. The final model, which had been trained with 1033 instances of the data, was used to draw conclusions about the entire collection of approximately 700,000 tiles that covered Sumba Island. With a confidence score greater than 0.5 after computation, a total of 22,397 traditional houses were identified. Post-copy expulsion, 19,143 things remained. A careful GIS assessment, using BING satellite symbolism as a base guide, uncovered cases of bogus up-sides — protests erroneously recognized as customary houses, principally connected with low certainty scores close 0.5.

An end limit of 0.8 was executed, limiting bogus negatives. A few clear misleading up-sides in open spaces, similar to rice fields, were brought about by disconnected trees creating shaded areas looking like house rooftop towers, or in stream talwegs, where shadows from rocks reflected the presence of houses. These problems were fixed by hand, and known administrative buildings and resorts built in the traditional Sumbanese style were taken out. However, due to rare images of poor quality or out-of-date satellite imagery, the method may overlook some large houses in the field.

IV.2 QUALITY ANALYSIS

The quality analysis comparison in Table 1 provides overview of various techniques employed for detecting the cultural heritage of vernacular houses in Sumba Island, Indonesia. In the realm of accuracy, traditional techniques like decision tree, k-nearest neighbor, neural network, svr, and random forest exhibit range from 66.356% to 70.581%. Transitioning to advanced object detection models, such as ssd_inception_v2, ssd_resnet_50_fpn, Faster_rcnn_inception_v2, Faster_rcnn_resnet50, and Faster_rcnn_resnet101, results in incremental accuracy improvement, ranging from 71.637% to 75.862%. However, the proposed BSTO-VGG16-ALNN technique stands out with a substantial accuracy of 96.235%, shows a remarkable increase in precision compared to both traditional and advanced approaches. Precision, representing the true positives among the predicted positives, is a critical metric. Traditional techniques exhibit precision values ranging from 62.859% to 67.084%. Advanced models, while generally improving precision, still fall short of the proposed technique. BSTO-VGG16-ALNN technique achieves a precision of 95.689%, showcasing a substantial improvement over both traditional and advanced methods. Recall, highlighting the true positives among the actual positives, is equally crucial. Traditional techniques demonstrate recall values from 62.639% to 71.089%, with random forest achieving the highest recall among traditional methods.

Advanced models surpass traditional methods, with recall ranging from 67.920% to 72.145%. However, our BSTO-VGG16-ALNN technique achieves an outstanding recall of 94.865%, signifying a substantial percentage-wise increase compared to all other techniques. F-measure, representing the harmonic mean of precision and recall, offers a balanced view. Traditional methods exhibit F-measure values ranging from 62.749% to 71.199%, with random forest again leading among traditional techniques. Advanced models enhance F-measure, ranging from 68.030% to 72.255%. Notably, the BSTO-VGG16-ALNN technique achieves a remarkable F-measure of 95.275%, shows significant improvement over existing techniques. AUC, measuring the area under the receiver operating characteristic curve, provides insight into overall model performance. Traditional techniques exhibit AUC values ranging from 62.639% to 66.864%. Advanced models improve AUC, ranging from 67.920% to 72.145%. Once again, the proposed BSTO-VGG16-ALNN technique excels with an AUC of 95.025%, demonstrating substantial improvement over existing techniques. Fig. 2 highlights the superior performance of the proposed BSTO-VGG16-ALNN technique across multiple metrics

Table 1: Quality measure analysis comparison.

Techniques	Values in %				
	Accuracy	Precision	Recall	F-measure	AUC
	Training				
Decision tree	66.356	62.859	62.639	62.749	62.639
k-nearest neighbor	67.412	63.915	63.695	63.805	63.695
Neural network	68.469	64.972	64.752	64.861	64.752
SVR	69.525	66.028	65.808	65.918	65.808
Random forest	70.581	67.084	66.864	66.974	66.864
Ssd_inception_v2	71.637	68.140	67.920	68.030	67.920
Ssd_resnet_50_fpn	72.693	69.196	68.976	69.086	68.976
Faster_rcnn_inception_v2	73.750	70.253	70.033	70.142	70.033
Faster_rcnn_resnet50	74.806	71.309	71.089	71.199	71.089
Faster_rcnn_resnet101	75.862	72.365	72.145	72.255	72.145
BSTO-VGG16-ALNN	96.235	95.689	94.865	95.275	95.025
	Testing				
Decision tree	68.729	68.056	66.733	67.388	64.091
k-nearest neighbor	69.785	69.112	67.789	68.445	65.147
Neural network	70.842	70.169	68.846	69.501	66.204
SVR	71.898	71.225	69.902	70.557	67.260
Random forest	72.954	72.281	70.958	71.613	68.316
Ssd_inception_v2	74.010	73.337	72.014	72.670	69.372
Ssd_resnet_50_fpn	75.066	74.393	73.070	73.726	70.428
Faster_rcnn_inception_v2	76.123	75.450	74.127	74.782	71.485
Faster_rcnn_resnet50	77.179	76.506	75.183	75.839	72.541
Faster_rcnn_resnet101	78.235	77.562	76.239	76.895	73.597
BSTO-VGG16-ALNN	96.985	96.012	95.867	95.939	95.865

Source: Authors, (2026).

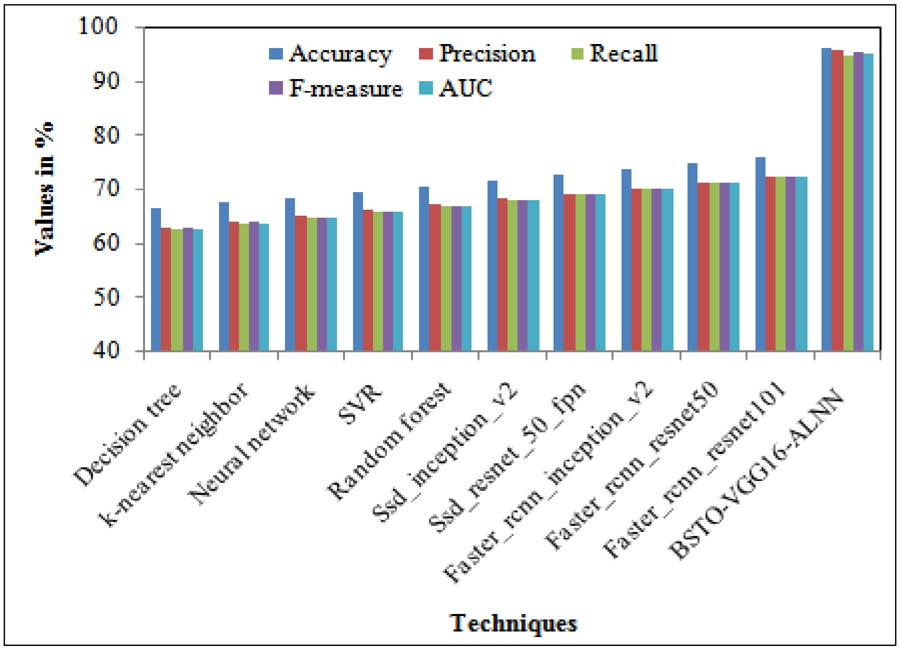

Figure 2: Quality analysis comparison for training samples.
Source: Authors, (2026).

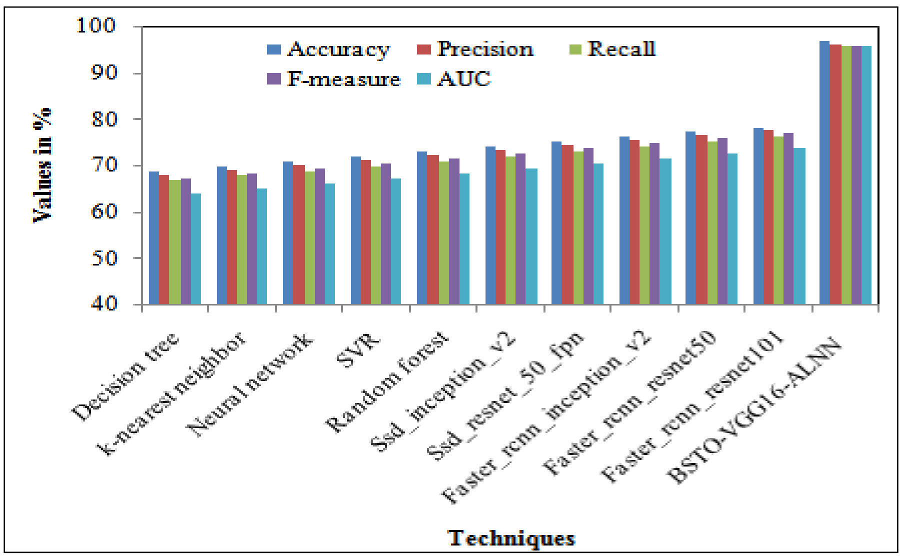

Figure 3: Quality analysis comparison for testing samples.
Source: Authors, (2026).

The quality analysis comparison in Figure 3 focuses on testing samples and provides an in-depth examination of various techniques employed for detecting the cultural heritage of vernacular houses in Sumba Island, Indonesia. In terms of testing performance, traditional techniques such as decision tree, k-nearest neighbor, neural network, SVR, and random forest exhibit accuracy values ranging from 68.729% to 72.954%. Notably, random forest demonstrates the highest accuracy among traditional methods. Transitioning to advanced object detection models, such as ssd_inception_v2, ssd_resnet_50_fpn, Faster_rcnn_inception_v2, Faster_rcnn_resnet50, and Faster_rcnn_resnet101, results in incremental accuracy improvements, ranging from 74.010% to 78.235%. However, the proposed BSTO-VGG16-ALNN technique stands out with a substantial accuracy of 96.985%, shows improvement in precision compared to both traditional and advanced approaches. Traditional techniques exhibit precision values ranging from 68.056% to 72.281%. Advanced models, while generally improving precision, still fall short of the proposed technique. BSTO-VGG16-ALNN technique achieves precision of 96.012%, shows improvement over both traditional and advanced methods. Moving on to recall, highlighting true positives among actual positives, traditional techniques demonstrate recall values from 66.733% to 76.239%, with random forest leading among traditional methods. Advanced models surpass traditional methods, with recall ranging from 72.014% to 76.895%. However, the proposed BSTO-VGG16-ALNN technique achieves an outstanding recall of 95.867%, improvement compared to other techniques. Traditional methods exhibit F-measure values ranging from 67.388% to 75.839%, with random forest again leading among traditional techniques.

Advanced models enhance F-measure, ranging from 72.670% to 76.895%. BSTO-VGG16-ALNN achieves F-measure of 95.939%, shows improvement over existing techniques. Traditional techniques exhibit AUC values ranging from 64.091% to 68.316%. Advanced models improve AUC, ranging from 69.372% to 73.597%. Once again, our BSTO-VGG16-ALNN technique excels with AUC of 95.865%, demonstrating substantial improvement over traditional and advanced approaches.

IV.3 ERROR ANALYSIS

Table 2 presents a comprehensive analysis of error measures, including R-squared (R2), mean relative error (MRE), and max relative error (MaxRE), for various techniques employed in the detection of cultural heritage in Sumba Island, Indonesia. Fig. 4 provides an in-depth analysis of error measures for various techniques employed during the training phase in the cultural heritage detection. In terms of R2, a measure of goodness of fit, traditional techniques such as decision tree, k-nearest neighbor, neural network, SVR, and random forest exhibit values ranging from 0.704 to 0.793. Advanced object detection models, including ssd_inception_v2, ssd_resnet_50_fpn, Faster_rcnn_inception_v2, Faster_rcnn Resnet50, and Faster_rcnn Resnet 101, show incremental improvements in R2, ranging from 0.795 to 0.837. Significantly, the proposed BSTO-VGG16-ALNN technique outperforms all others with an impressive R2 of 0.912, indicating a substantial increase in the model's ability to explain the variability in the data. Traditional techniques demonstrate MRE values ranging from 5.470% to 8.700%. Advanced models generally improve MRE, ranging from 5.220% to 6.700%. The proposed BSTO-VGG16-ALNN technique excels with a remarkably low MRE of 3.235%, shows a substantial decrease compared to all other techniques. MaxRE, representing the maximum difference between predicted and observed values, follows a similar trend. Traditional techniques exhibit MaxRE values ranging from 10.040% to 26.900%. Advanced models, while improving, still have MaxRE values ranging from 6.366% to 19.300%. BSTO-VGG16-ALNN technique stands out with low MaxRE of 6.366%, shows significant improvement compared to all other techniques.

Table 2: Error measure analysis comparison.

Techniques	Values in %			Values in %		
	R^2	MRE	MaxRE	R^2	MRE	MaxRE
	Without PCA			With PCA		
Decision tree	0.704	8.400	26.900	0.764	7.500	20.000
k-nearest neighbor	0.859	5.700	17.700	0.859	5.500	19.600
Neural network	0.673	8.700	21.800	0.840	5.900	18.700
SVR	0.787	6.600	17.700	0.870	5.100	16.500
Random forest	0.793	6.700	19.300	0.818	5.900	18.300
Ssd_inception_v2	0.795	6.470	16.120	0.866	4.900	16.670
Ssd_resnet_50_fpn	0.806	6.220	14.600	0.878	4.540	16.020
Faster_rcnn_inception_v2	0.816	5.970	13.080	0.890	4.180	15.370
Faster_rcnn_resnet50	0.827	5.720	11.560	0.902	3.820	14.720
Faster_rcnn_resnet101	0.837	5.470	10.040	0.914	3.460	14.070
BSTO-VGG16-ALNN	0.912	3.235	6.366	0.929	2.235	5.896

Source: Authors, (2026).

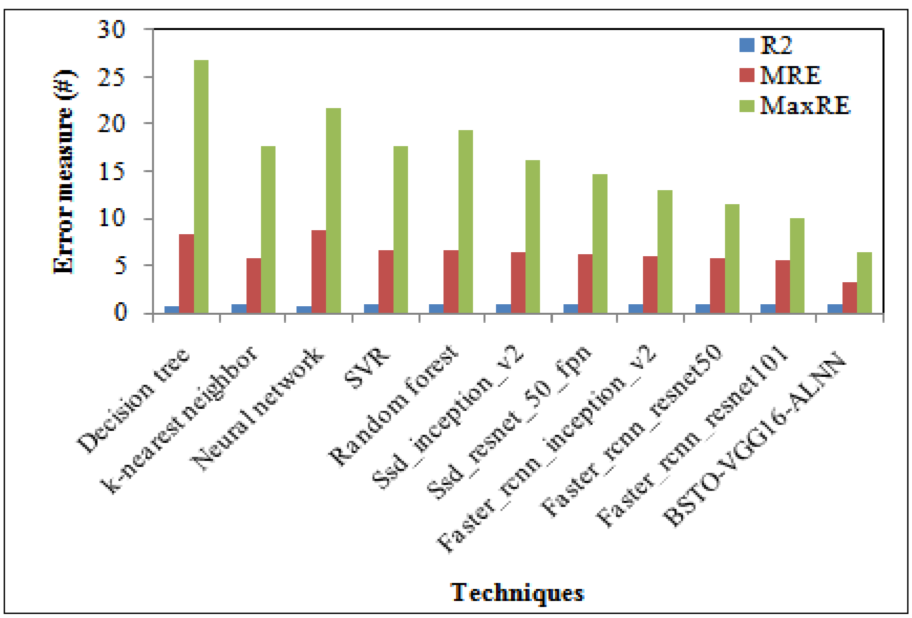

Figure 4: Error analysis comparison for training samples.
Source: Authors, (2026).

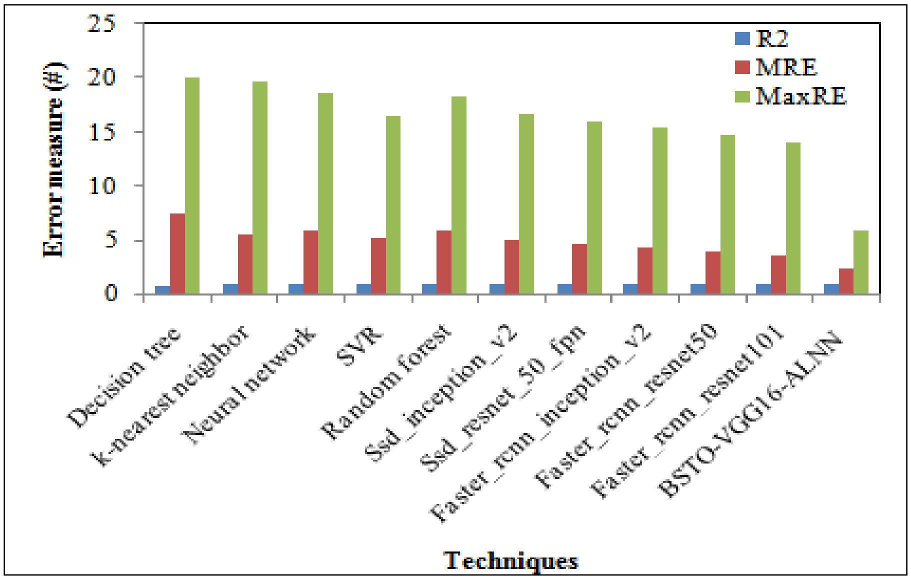

Figure 5: Error analysis comparison for testing samples.
Source: Authors, (2026).

Figure 5 presents error analysis for testing samples across various techniques employed in the cultural heritage detection task. Beginning with R^2, which measures the goodness of fit, traditional techniques like decision tree, k-nearest neighbor, neural network, SVR, and random forest exhibit values ranging from 0.764 to 0.870. Advanced models, such as ssd_inception_v2, ssd_resnet_50_fpn, Faster_rcnn_inception_v2, Faster_rcnn_ resnet50, and Faster_rcnn Resnet 101, show further improvements, ranging from 0.866 to 0.914. Notably, the proposed BSTO-VGG16-ALNN technique stands out with an impressive R2 of 0.929, shows a superior ability to explain the variability in the testing data. Traditional techniques show MRE values ranging from 5.1% to 7.5%, while advanced models generally improve MRE, ranging from 3.46% to 5.9%. BSTO-VGG16-ALNN technique excels with low MRE of 2.235%, shows improvements compared to other techniques. MaxRE, representing the maximum difference between predicted and observed values, follows a similar trend. Traditional techniques exhibit MaxRE values ranging from 14.07% to 20%, while advanced models, though showing improvement; still have MaxRE values ranging from 5.896% to 18.670%. The BSTO-VGG16-ALNN technique stands out with an exceptionally low MaxRE of 5.896%, show a significant improvements decrease compared to all other techniques.

V. CONCLUSION

We have introduced an approach employing advanced technologies for the detection of cultural heritage in the form of vernacular houses in Sumba Island, Indonesia. Our method integrates deep learning techniques and big data analytics to enhance the accuracy and efficiency of cultural heritage detection. The application of the boosted sooty tern optimization (BSTO) algorithm proves effective in precisely segmenting vernacular houses from remote sensing images, showcasing a crucial initial step in our methodology. Leveraging the pre-trained VGG-16 architecture allows us to extract intricate features from the segmented target image, enhancing the depth of our analysis. The subsequent implementation of the hybrid adaptive learning neural network (ALNN) ensures the automatic and precise detection of vernacular houses. Through thorough validation using Sumba Island tiles, our BSTO-ALNN technique shows compelling results, underscoring its effectiveness in accurately identifying and preserving cultural heritage. This method contributes to the broader field of cultural heritage preservation, offering robust and technologically advanced solution for detecting and safeguarding vernacular houses in diverse landscapes such as Sumba Island.

VI. AUTHOR’S CONTRIBUTION

Conceptualization: P. Nandhini.
Methodology: P. Nandhini.
Investigation: P. Nandhini.
Discussion of results: P. Nandhini.
Writing – Original Draft: P. Nandhini.
Writing – Review and Editing: P. Nandhini.
Resources: P. Nandhini.
Supervision: P. Nandhini.
Approval of the final text: P. Nandhini.

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