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Artificial Neural Network for Predicting Edge Stretchability in Hole Expansion Test With Gpa-Grade Steel

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ABSTRACT This paper mainly proposes an artificial neural network (ANN) model for predicting edge stretchability of GPa-grade steels, which is substantially difficult to predict due to the complex nonlinear relation among the numerous sheared edge qualities. We newly suggest the physically characterized parameters, such as material properties, deformed shape, and work hardening of sheared edge, to predict the various materials and punching methods, simultaneously. The proposed parameters are trained with the pre-damage strain which is calculated by inherent fracture strain and experimental results in terms of hole expansion ratio. To prevent the overfitting issues, cross validation method with additional datasets from a different kind of edge stretchability test such as sheared edge tensioning test are utilized. Experimental validations have been conducted with various GPa-grade steels and sheared edge conditions, which are compared with the proposed ANN model and numerical simulation. The proposed ANN model exhibits remarkable performance in the prediction of hole expansion ratio having a mean absolute error of 1.5% when compared to the previous studies such as numerical simulation and ANN model with utilizing the maximum hardness measured at the sheared edge.

INDEX TERMS Artificial neural network, edge cracking, edge stretchability, GPa-grade steels, sheared edge quality.

I. INTRODUCTION

GPa-grade steels which exhibit an ultimate tensile strength of at least 1,000 MPa have been widely applied to body-in-white (BIW) structures to improve their crash worthiness and reduce their weight [1]–[3]. However, undesired fractures frequently occur during the stamping and flanging process due to the poor formability and sheared edge stretchability of GPa-grade steels, which restricts their wide application in BIW panels [4], [5]. It is difficult to predict edge cracking using numerical simulations with conventional forming limit curves since the onset of edge cracking occurs at a significantly lower strain than that of the forming limit curves, which causes significant delays in new product development [5], [6]. Moreover, edge cracking is still being reported in the third-generation advanced high-strength steels which have been recently developed to obtain superior elongation while maintaining inherent strength [7]–[9]. For these reasons, the prediction of edge cracking is an enormous challenge for the wide application of GPa-grade steels in BIW structures.

Edge cracking is predominantly affected by the sheared edge qualities after the punching or shearing processes that produce the initial blanks from coiled sheet steel. Sheared edge quality related to the edge cracking can be categorized into material hardening and deformed shape of sheared edge [10]–[12]. The deformed shape of sheared edge typically consists of roll over, sheared, fracture, and burr zones [13]. Material hardening represents the strain hardening profile along the sheared edge after the shearing [14]. Extensive studies have been mainly conducted by numerical analysis with pre-defining the newly proposed pre-damage values.

Wang *et al.* [15] proposed a numerical model for predicting the hole expansion ratio (HER) by mapping a pre-damage value at the center of the sheared edge after punching numerical analysis. However, it cannot distinguish the various die clearance conditions since this model only concerns a single

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influencing factor. Mu *et al.* [16] suggested the edge cracking prediction method using uncoupled ductile fracture models by proposing a pre-damage value consisting of a function of the equivalent plastic strain and the strain at the onset of the fracture. However, it is limited to predict the exact experimental tendency of edge cracking with respect to the punching clearances, since it cannot consider the complex nonlinear effects among the various sheared edge qualities due to the definition of pre-damage only relied on the numerical punching analysis. Pathak [17] suggested pre-damage value using 3-dimentional X-ray computed tomography for capturing the number of voids per unit volume after punching process, which could precisely represent the edge cracking by considering the void growth and their coalescence. Despite their good prediction accuracy, this method is limited to utilize due to the high costs and time to obtain dataset, which makes it possible to apply to various applications. He *et al.* [18] recently proposed an experimental method for defining the pre-damage using the hardness (HV) to characterize the work hardening with respect to the punching clearances. They suggested that a single maximum HV can effectively predict the various die clearance in punching process with a new flat punch.

Based on the literature reviews, experimental methods to define a single pre-damage value have been recently developed. However, the punching process inevitably undergoes tool wear after repetitive punching process due to the excessive contact force [19], which aggravates the deformed shape with the onset of a severe burr. In addition, advanced punching methods such as humped bottom punch and two-stage punching have been newly developed to reduce the material hardening at the sheared edge [7], [8]. Under these circumstances, it is highly required to find the effective experimental pre-damage values to predict the edge stretchability of various punching methods.

However, there are several obstacles to apply all the sheared edge qualities for predicting edge cracking, since it does not only be clarified the exact relationship between numerous sheared edge qualities and edge cracking mechanism, but also has a complex and nonlinear relationship among the various sheared edge qualities [5], [12], [16], [18]. To mitigate these difficulties, artificial neural network (ANN) is one of the most widely utilized deep learning algorithms to predict the nonlinear relationships between multiple inputs and output data in various manufacturing fields [20]–[22]. Recent research trends in development of ANN model for engineering field are finding a definition of physically meaning variables and obtaining the good accuracy with limited amount of data.

For example, Lu *et al.* [23] developed an ANN model for predicting mechanical properties from instrumented indentation by integrating the numerical simulation and experimental data to increase the datasets to achieve a high accuracy. They defined the physically characterized input variables suing the indentation response from indentation instrument and physical and scientific law. Leema *et al.* [24] found physically meaningful datasets from the various material testing methods such as X-ray diffraction analysis, particle size analysis, transmission electron microscope, scanning electron microscope and energy dispersive spectrum, which are applied for the ANN model to investigate the effects of materials and processing conditions on the final properties of a powder metallurgy process. Lee *et al.* [25] integrated the constitutive equation and an ANN model to study the relationship between certain powder design parameters and compaction properties. In addition, they utilized the leave one out cross validation method to minimize the overfitting problem due to the less data, which makes it possible to show a good prediction accuracy even with utilizing a limited amount of data.

In manufacturing fields, the recently developed ANN models mainly focused on the proposing the physically characterized variables specialized in each manufacturing fields using experimental and image data with integrating physical law. In addition, new approach to overcome the lack of dataset are proposed to achieve good prediction accuracy and minimize the overfitting. Since there is no report of the ANN model for predicting the edge stretchability with respect to the sheared edge qualities induced by various punching conditions, it is highly required to establish the physically characterized input variables and proper ANN approach to achieve the remarkable prediction accuracy.

This paper newly proposes an ANN model to predict edge stretchability in terms of HER with GPa-grade steels with respect to the various punching conditions and materials. New physically characterized input variables are proposed based on the experimental results and well-known physical law, which are partitioned in three representative sheared edge quality parameters such as material properties, material hardening, and deformed shape of sheared edge. Pre-damage value obtained from hole expansion (HE) are newly defined and applied for the output data for training with the complex combination and nonreality of factors in sheared edge qualities. To achieve the remarkable prediction accuracy, we newly suggested the ANN approach by utilizing sheared edge tensioning (SET) test dataset, which is totally different method in edge stretchability tests. The performance of the proposed ANN model is evaluated by direct comparison with experimental results in terms of HER for different GPa-grade steels and blanking methods including humped bottom punch and two-stage punching.

The rest of the paper is organized as follow: In Section II, we present the new experimental datasets to predict various sheared edge qualities by categorizing the input parameters based on the physically meanings related to the edge cracking. Section III focuses on the proposed ANN prediction framework which is validated by comparison with previous research such as numerical prediction and other prediction methods. Finally, Section IV concludes the paper with summarizing the results and findings.

II. EXPERIMENTAL PROCEDURE

In order to predict the predict the edge stretchability with various materials and punching methods, it is highly required to take into consideration of the complex combination of numerous factors in sheared edge qualities. However, it is difficult to predict the edge stretchability using all factors, since prediction accuracy can be deteriorated when unknown trivial variables are applied. For these reasons, it is essential to define the physically related influencing factors on edge stretchability.

Figure 1 demonstrates the flow chart for predicting the edge stretchability in this paper, and sheared edge qualities are categorized into three representative parameters such as material testing, deformed shape, and material hardening data. We proposed the physically characterized input features for each parameter. First, material testing parameter indicates the inherent material characteristics which is examined by the flow curves obtained from the uniaxial tensile tests. Second, deformed shape parameter represents the characteristics of deformed shape in sheared edge after punching process obtained from the vision system, which shape is directly affected by the condition of punching process. Last, material hardening parameter indicates the strain hardening along the sheared edge induced by the severe plastic deformation after punching process, which significantly changes with respect to the condition of punching process and applied materials. The proposed input features for each parameter are matched with the results of edge stretchability tests in terms of pre-damage strain to train the complex combination and nonlinearity among the data.

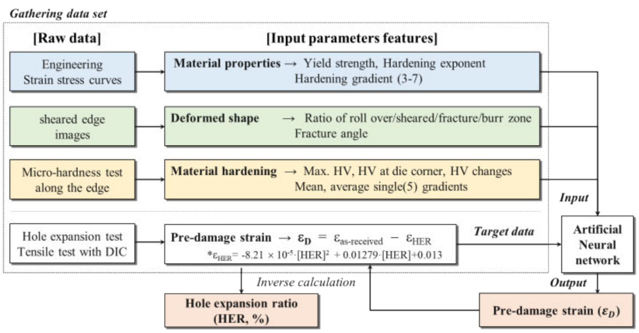

FIGURE 1. Flow chart for predicting edge stretchability with ANN model.

A. MATERIAL TESTING DATA

Although specific materials are located in the same category of GPa-grade steels, they show various strain hardening behavior depending on the chemical composition and heat treatment as shown in Fig. 2. Figure 2 demonstrates the engineering strain-stress curves of two different GPa-grade steels with XF980 and TRIP1180. TRIP1180 is one of the conventional GPa-grade steels which is widely applied in BIW panels, and XF980 is categorized as a third-generation advanced high-strength steel exhibiting a good strength-ductility combination [8], [9].

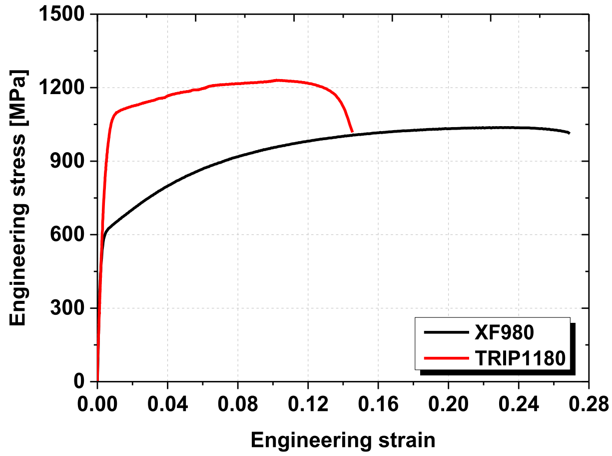

FIGURE 2. Flow curves of XF980 and TRIP1180 after tensile tests.

It has been reported that inherent material properties such as yield strength and strain hardening exponent affect the work hardening and deformed shape of sheared edge [12], [18]. Yield strength represents the onset of plastic deformation, which determines the geometrical deformed shapes of sheared edges since a higher yield strength reflects the onset point at which the punch penetrates through the thickness direction. The strain hardening exponent represents the strain hardening tendency during plastic deformation, and GPa-grades steels with a higher strain hardening exponent tends to undergo more severe plastic deformation around the sheared edges. It can be calculated by the power law equation as expressed in Eq. (1):

$$\sigma = K \times \varepsilon^n \tag{1}$$

where K and n denote the strength coefficient and hardening exponent, respectively, which are listed in Table 1. However, it is insufficient to express the strain hardening characteristics to precisely evaluate the strain hardening characteristics, since it changes rapidly from initial yielding to ultimate tensile strength. To evaluate the initial strain hardening characteristics in detail, the mean gradient for each section was calculated by partitioning 5 sections from yield strength to ultimate tensile strength as shown in Fig. 3, which are additionally adopted for the input features of material hardening including conventional input features such as yield strength and strain hardening exponent.

TABLE 1. Material properties of XF980 and TRIP1180.

	XF980	TRIP1180
Yield strength (MPa)	629	1087
Flow curves ($\sigma = K \times \varepsilon^n$)	$\sigma = 1899.8 \times \varepsilon^{0.2522}$	$\sigma = 1519.3 \times \varepsilon^{0.071}$
Strain hardening exponent (n)	0.2522	0.071

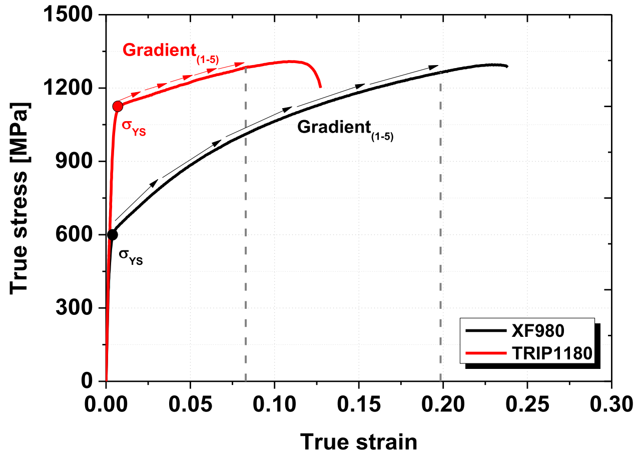

FIGURE 3. Input features for representing material properties.

In order to obtain the proposed features in the material testing parameter, raw engineering strain-stress dataset is required, which can be easily converted to the true-strain stress dataset, and yield strength and strain hardening coefficient can be calculated using mathematical programs. Then, the gradient of ranges from yield strength to ultimate tensile strength, which are shown in Figure 3, can be extracted as a profile of deviation between pairs of fixed-range points by a program developed using Python language.

B. GEOMETRICAL DATA IN THE DEFORMED SHAPE

The deformed shape of a sheared edge is one of well-known influencing factors on edge stretchability [14], which are examined by utilizing vision system to capture front or cross-sectional view of sheared edge as shown in Fig. 4. Figure 4 demonstrates a representative deformed shape of a sheared edge, and geometrical data are examined by analyzing the image processing algorithm. Sheared edge along the thickness is respectively partitioned into 4 zones, such as roll over zone, sheared zone, fracture zone, and burr zone as shown in Fig. 3(a). From the previous literature, the ratio of partitioned zone and size of burr are widely utilized to examine the deterioration of edge stretchability in terms of HER [15], [26]–[27]. For example, HER begins to decrease as the burr is formed, which gradually worsens in proportion to the size of burr. A lower portion of the fracture zone shows a poor HER. To consider the effect of various geometric data of deformed shape on edge stretchability, the length of roll over, sheared zone, fracture zone, burr zone, and fracture angles are normalized by original thickness and 90°, which is adopted for the input features for representing deformed shape parameter.

The length of each zones can be calculated as the vertical distances between end points as red scatters shown in Fig. 4(c), which can be precisely located by an image processing-based program developed to position required points regarding to the gradient change of top, bottom and side curves of the specimen.

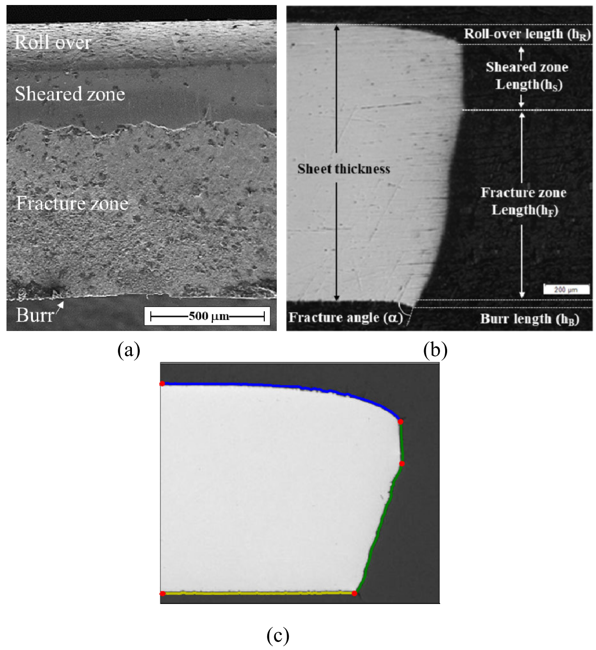

FIGURE 4. Geometrical characteristics of a sheared edge: (a) definition of sheared edge; (b) cross-sectional view; (c) end point measurement for extracting features.

C. MATERIAL HARDENING DATA

Inevitably, GPa-grade steels undergo severe plastic deformation at the sheared edge during the punching process in which uneven local hardening is distributed along the sheared edge through the thickness direction. It is generally evaluated by the Vickers hardness test to characterize the local plastic deformation of sheared edge in detail. A higher hardness value indicates that the sheared edge undergoes severe strain hardening, which in turn means that the residual local formability is low to withstand the edge stretching during stamping and flanging process. To examine the level of the damage in the shear edge, an edge strain hardening (ESH) index is adopted as defined in (2) where $HV_{\text{as-received}}$ indicates the HV of as received material measured away from the sheared edge.

$$ESH = (HV - HV_{as-received})/(HV_{as-received}) \tag{2}$$

Maximum HV among the sheared edge is frequently utilized to predict the edge stretchability of GPa-grade steels to characterize the representative pre-damage strain [18]. However, it is not proper to apply for the advanced punching method such as humped bottom punch and two-stage punching which show remarkable improvements in HER compared to the flat punch, since advanced punching methods can improve the HER by dramatically reducing the hardness at the bottom of fracture zone, although the maximum hardness is similar to the conventional punch as shown in Fig. 5 [8], [9].

Under these circumstances, it is highly required to fully consider the hardness profile along the sheared edge to predict the HER, precisely. Vickers hardness tests have been performed along the sheared surface measured with every 0.1 mm interval from burr to roll over zone to obtain hardness profile, and we newly proposed new input features concerning the physical characteristics, such as hardness at bottom, hardness changes, each gradient of hardness changes and their mean and average gradient as shown in Fig. 5, which are adopted for the deep learning including maximum HV.

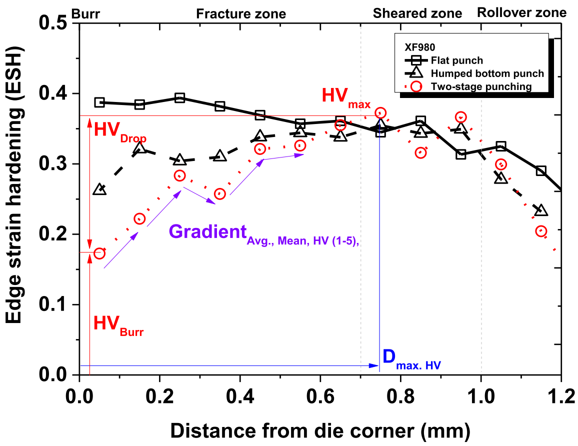

FIGURE 5. Input features for material hardening parameters.

To obtain the hardness profile, it is required to prepare the polished specimen after mounting for performing the Vickers hardness test along the sheared edge. the maximum HV and its position and HV at burr are firstly calculated, and then the dropped or increased HV can be calculated. The single, mean, average gradients of fracture zone as shown in Fig. 5 are extracted as a profile of deviation between pairs of fixed-range points by a program developed using Python language.

D. HOLE EXPANSION TESTS DATA

The hole expansion (HE) is one of the most widely utilized evaluation methods to examine edge cracking resistance in terms of edge stretchability in which a conical punch expands punched hole out-of-plane until fracture occurs through the thickness direction of the sheared edge. Figure 6 demonstrates the HE experimental set-up with machine vision system, which we conducted by following the definition of ISO 16630-2009 standard. Since an edge crack suddenly propagates through the sheared edge rapidly, real-time inspection system using a monochrome CCD camera with 5M pixels is utilized to precisely evaluate the through-thickness cracks [28].

To evaluate the edge stretchability quantitatively, the HER is measured by calculating the ratio of the initial diameter and the final diameter at which a crack fully propagates through the thickness direction as defined in (3)

$$HER(\%) = ((D_F - D_0)/(D_0)) \times 100 \tag{3}$$

where D_0 and D_F denote the initial and final diameter, respectively. As the initial sheared edge exhibits the larger HER, it represents good edge stretchability. However, since it is not possible to directly express the pre-damage of a sheared

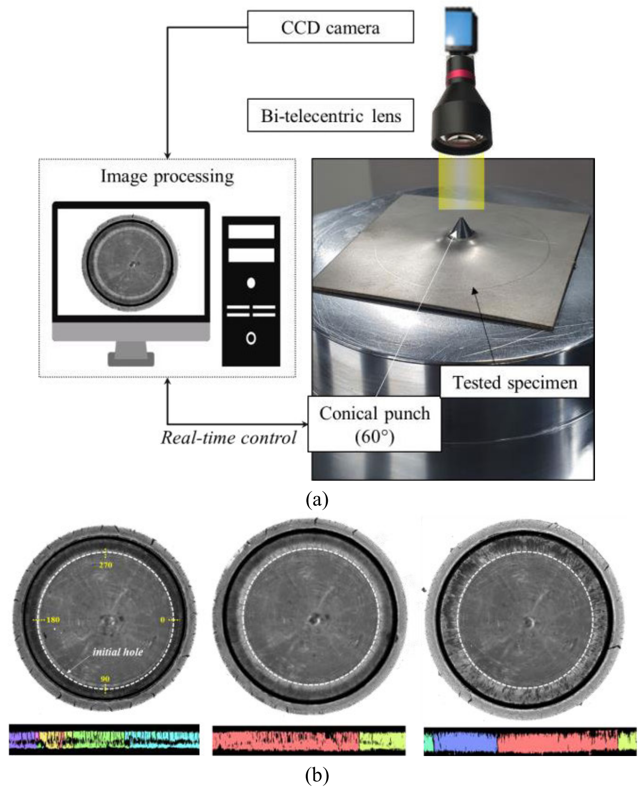

FIGURE 6. Experimental set up for hole expansion test with machine vision system: (a) experimental set-up; (b) HER measurement using real time image process.

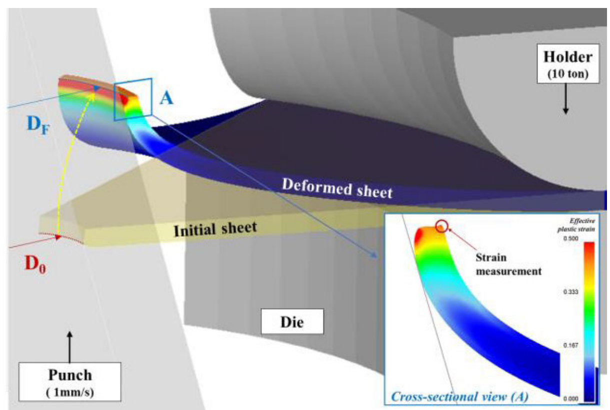

FIGURE 7. Correlation between HER and the effective plastic strain.

edge, it is necessary to find a relationship between HER and the plastic strain at the sheared edge. Figure 7 schematically illustrates the HE tests analysis, which was numerically simulated with the DEFORM-2D commercial software. An initial sheet of XF980 with a thickness of 1.2 mm was modelled with 30,721 axisymmetric elements, which were coupled with the punching analyses to simulate the geometrical shape after the punching process. The equivalent plastic strain at the burr element was traced corresponding to the HER as expressed in (4), then the pre-damage strain at the sheared edge was calculated by the fracture strain of the as-received material, and the equivalent plastic strain was obtained from the HER as defined in (5):

$$\varepsilon_{HER} = -8.21 \times 10^{-5}[HER]^2 + 12.79 \times 10^{-3}[HER] + 0.013 \quad (4)$$

$$\varepsilon_D = \varepsilon_{as-received} - \varepsilon_{HER} \quad (5)$$

where ε_D and ε_{HER} indicate the pre-damage strain and the equivalent plastic strain from the HER, respectively. $\varepsilon_{as-received}$ denotes the fracture strain of the as-received material, which was obtained from the uniaxial tension test using a digital image correlation technique supported by GOM ARAMIS v6.0. The calculated ε_D was utilized for output data to find a nonlinear relationship with the sheared edge qualities.

III. PREDICTION OF HOLE EXPANSION RATIO

A. ARTIFICIAL NEURAL NETWORK(ANN) MODEL

An ANN algorithm is applied to predict the edge stretchability of GPa-grade steels for various material hardening and punching conditions with 72 experimental data set. Additional 216 data-sets of SET test, which is one of edge stretchability methods by tensioning the tensile specimen with sheared induced on one side of edge, is applied to increase the training efficiency since the SET test is also affected by the material properties and material hardening in terms of strain hardening exponent and material hardening profile [8], [9]. In a single data set, 23 input features for representing three parameters as listed in Table 2, which are corresponded with the output feature of the pre-damage strain. Figure 8 shows the schematic diagram for representing overall HER prediction system to consist the ANN model.

TABLE 2. Input parameters and their detailed features for ANN model.

	Material properties	Deformed shape	Material hardening
Input features	1. Yield strength 2. Strain hardening exponent 3-7. Strain gradients	1. Ratio of roll over 2. Ratio of sheared 3. Ratio of fracture 4. Ratio of burr 5. Fracture angle	1. Max. HV 2. HV at die corner 3. HV changes 4. Position of max. HV 5. Mean gradient 6. Average gradient 7-11. single gradient

Figure 9 presents the schematic diagram of the ANN, which is constructed with the complex combination of multiple neurons. Each input cell receives the individual inputs [25], which are applied to calculate the intermediate outputs by applying weights factors using the transfer function as expressed in (6):

$$net_j = \sum\nolimits_{i=1}^{n} (x_i w_{ij} + b) \quad (6)$$

where x_i and w_{ij} denote input and weighting factors, respectively. b and n indicate the bias and the number of input features, respectively. Net_j is the transfer function to get the final output of the neural cell. In order to calculate the

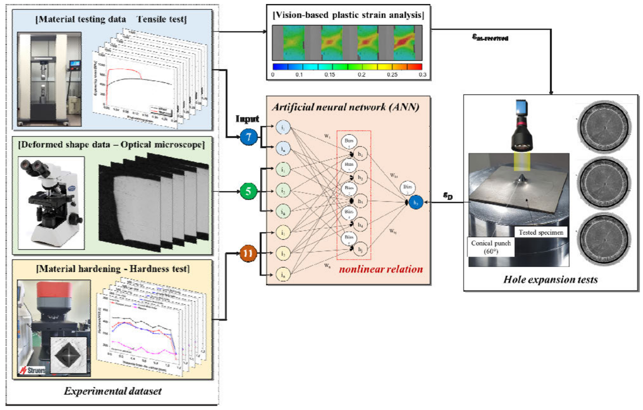

FIGURE 8. Overall structure of ANN model for prediction of HER.

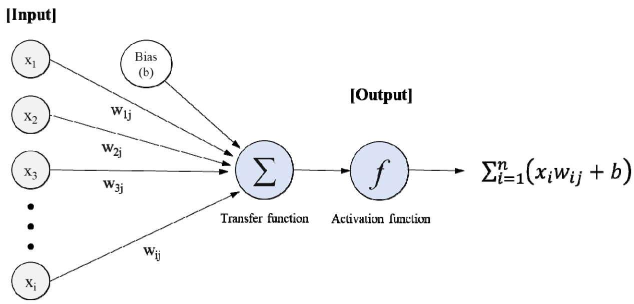

FIGURE 9. Schematic diagram of basic neural cells in a neural network.

non-linearity between the input and output data, rectified linear units (ReLU), as defined in (7), was applied for the ANN model in consideration of the effect of the occurrence of the burr formation, which can also reduce the so-called gradient vanishing issue during deep learning.

$$y_j = f(net_j) = \begin{cases} 0 & \text{for } net_j < 0 \\ x & \text{for } net_j \geq 0 \end{cases} \quad (7)$$

We applied a multi-layered neural network structure as shown in Fig. 10, which consisted of an input layer, hidden layer, and output layer, and the hidden layer size was fixed

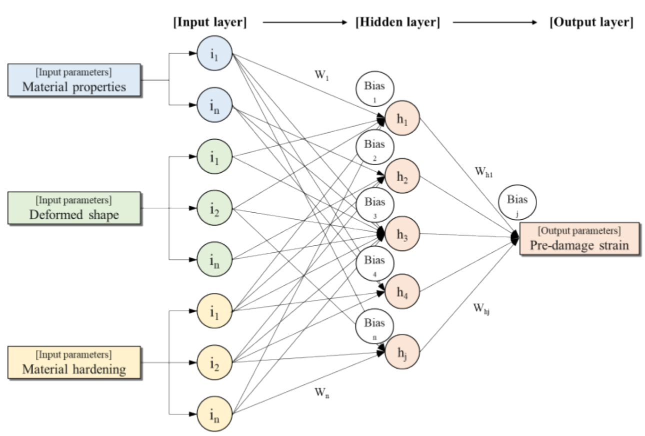

FIGURE 10. Architecture of the proposed ANN model.

at 60 neurons, which are determined by the trial and error methods by changing the number of hidden layer and their nodes to prevent the overfitting with securing the prediction accuracy. The input layer receives the input data for transferring the data set to the hidden layer. In the hidden layer, the numbers of layers and nodes are manually determined by evaluating the prediction performance, which is connected with every input node to find nonlinear relationship among the nodes. The weighting factors and biases are calculated by the transfer function and the activation function. Then, weighting factors and bias are optimized by a gradient descent algorithm to figure out the non-linear connections between the input and output data by minimizing the error in terms of root mean square error between the prediction results and the target value.

In order to increase the prediction accuracy, we conducted the cross validation for training to prevent the overfitting problems [25]. The prediction accuracy was evaluated by the mean absolute error (MAE) as defined in (8):

$$MAE = \frac{1}{n}\sum\nolimits_{i=1}^{n}\left|\varepsilon_{t\arg et} - \varepsilon_{pred.}\right| \quad (8)$$

where n indicates the total number of data samples. $\varepsilon_{\mathrm{target}}$ and $\varepsilon_{\mathrm{pred}}$ denote the target value and prediction value, respectively. In addition, correlation coefficients with the values obtained from experiments are compared with respect to the machine learning methods to examine the performance among the machine learning methods.

B. EFFECT OF INPUT FEATURES

In order to examine the effect of proposed input features as listed in Table 2, the performance of each input feature was examined in terms of MAE. To confirm the probability of usage of ANN as the utilized model via comparison with the other machine learning algorithms, the proposed method, which one after another is integrated the machine learning algorithms trained by the similar objects as training process of ANN model, was tested from the testing dataset with 40 different cases, which are compared with the various error statistics such as MAE, root mean squared error (RMSE), correlation coefficient test, and R-square (R^2). Based on the results obtained as shown in Table 3, ANN technique which officially preferred as the utilized model for the proposed method performed the highest correlation coefficient tested by comparing the error statistics such as predicted pre-damage strain and standard references obtained from experiments (r = 0.9348, p < 0.0001). The correlation between the proposed method and the standard measurement is shown in Fig 11. Figure 12 shows the prediction error in the trained ANN model with respect to the applied input features. It is interesting to note that the maximum HV, which is known to be a major influencing factor in edge cracking, exhibits significantly low prediction accuracy with MAE of 0.07, which only predicts the case of conventional flat punch. On the other hand, proposed each influencing factors remarkably improved the prediction accuracy.

TABLE 3. Comparison of correlation coefficient of testing cases between different machine learning algorithms.

Algorithms	MAE	RMSE	Corr. Coef. (p<0.0001)	R^2
Linear regression	0.033	0.040	0.8751	0.7758
Decision tree (D = 3)	0.031	0.037	0.8903	0.7927
Lasco Regression	0.033	0.040	0.8647	0.7487
Ridge regression	0.028	0.035	0.9082	0.8340
Support vector machine	0.063	0.070	0.7762	0.6124
Artificial neural network	0.023	0.031	0.9348	0.8738

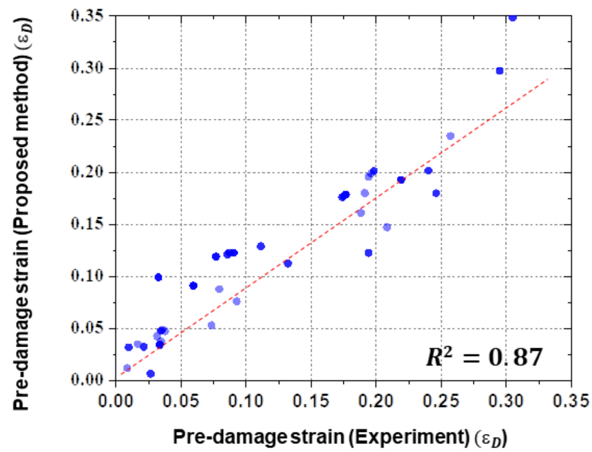

FIGURE 11. Scatterplots of correlation between experimental values and pre-damage strain evaluated by proposed method.

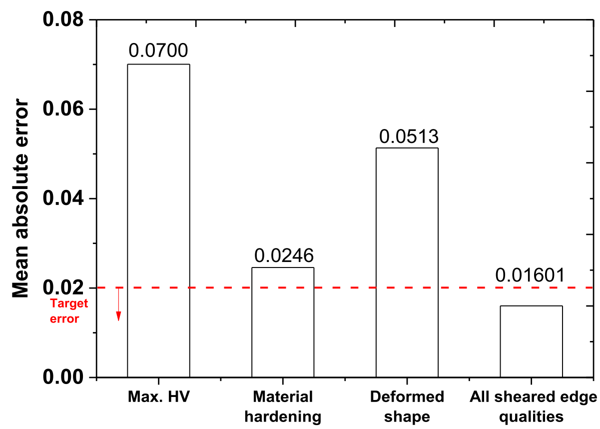

FIGURE 12. Error in trained ANN model with respect to the applied input features.

In order to investigate the reason of inaccurate prediction results only with maximum HV, deformation of sheared edge is observed by vision system during HE tests as shown in Fig. 13, which are analyzed with the results of hardness test as shown in Fig. 5. It is interesting to note that the onset time and position of tiny crack is mainly induced by maximum HV, but its propagation direction and speed are determined by the

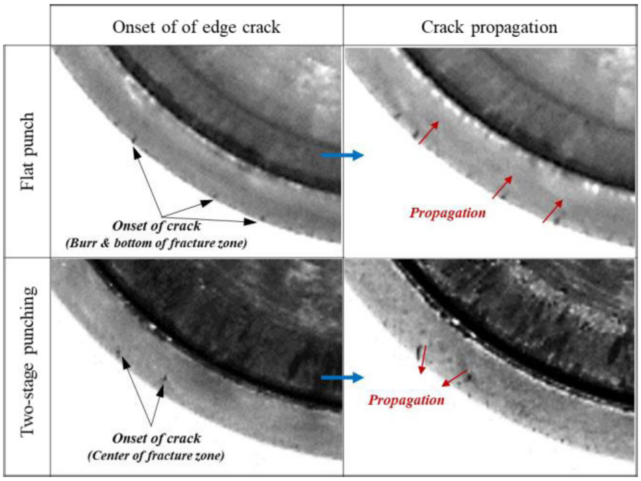

FIGURE 13. **Onset of crack and crack propagation during HE tests.**

various sheared edge qualities as shown in Fig. 13. This is why the proposed ANN with fully applying the suggested factors exhibits the best performance in prediction of pre-damage strain regardless of material hardening and punching methods, since it does not only consider the whole tends of accumulated work hardening after blanking with concerning material properties, but also take into consideration of the geometrical shape of deformed sheared edge which affects the onset of crack.

C. PREDICTED RESULTS OF HOLE EXPANSION RATIO

The final goal of the ANN model in this paper is prediction of HER regardless of material properties and blanking methods. It is possible to predict the residual edge stretchability in terms of ε_{HER} using predicted pre-damage strain using the Eq. (5), which can be inversely calculated for predicting HER based on the fitted Eq. (4). Figure 14(a) demonstrates the HER prediction results of the tested samples with the proposed ANN model by only training with HER data set, which is compared to the ANN model with maximum HV and experimental results. In order to compare the performance of proposed ANN model, numerical simulation has been carried out with the DEFORM-2D commercial software as mentioned in Section 2.D. Based on the previous literatures [18], pre-damage values are calculated with respect to the materials and punching methods utilizing the maximum HV obtained from the micro-hardness test. When maximum plastic strain at the burr reaches the fracture strain of as-received material, we treated that edge crack occurs. The numerical prediction results as depicted with red dash line are compared with the proposed ANN model as shown in Fig. 14.

We compared the effect of proposed pre-damage values and generally used single pre-damage value calculated by the maximum hardness. The pre-damage value with maximum HV can only predict the HER for the conventional flat punch using ANN model and numerical simulation, since there is little change in hardness at the fracture and sheared zone

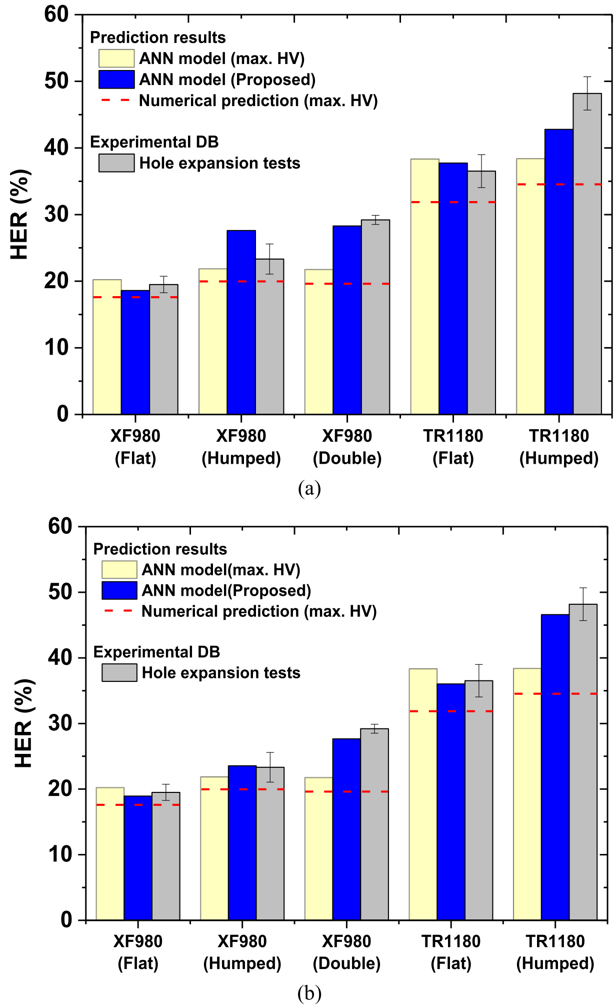

FIGURE 14. **Prediction results using ANN model with proposed sheared edge qualities: (a) HE tests data sets: (a) HE and SET test data sets.**

when applying the flat punch as shown in Fig. 5, which is supported by the previous literatures [18]. Numerical prediction using maximum HV also shows low prediction accuracy in advanced punching methods with all humped bottom punch and two-stage punching, since it is insufficient to express the complex enhancing mechanism of advanced blanking methods using maximum HV. On the other hand, it is possible to predict the advanced blanking methods by proposed ANN model with efficiently analyzing the changes in sheared edge qualities, such as hardness profile and the ratio of deformed shape in sheared edge. However, overestimation or underestimation of HER occurs when applying proposed ANN model only with HER dataset as shown in Fig. 14(a) due to the lack of training of nonlinearity and complex combination among the various sheared edge qualities.

In order to improve the remarkable prediction accuracy, proposed ANN model is additionally trained by proposed approach with utilizing SET test data set, which is totally different sheared edge stretchability tests in terms of shearing method and stretching direction. Figure 14(b) demonstrates the prediction results using HE and SET test datasets that the overestimation and underestimation problems are solved with representing exhibiting a 1.5% of HER difference. It is evaluated that training efficiency can be improved due to the similar enhanced mechanism of sheared edge stretchability although shearing method and stretching direction are different [8], [9].

It is possible to conclude that the proposed ANN model with physically characterized input parameters demonstrated the best performance in prediction of HER regardless of the material properties and blanking methods, and the prediction accuracy can be improved by utilizing a SET edge stretchability data set.

IV. CONCLUSION

This paper proposes ANN model to predict the edge stretchability of GPa-grade steels with suggesting the various sheared edge qualities based on physically characterized input parameters such as material properties, deformed shape, and material hardening. Cross validation has performed to prevent the overfitting, and SET data sets were additionally applied to efficiently train the nonlinearity among sheared edge qualities the input features. Experimental validation was carried out for three representative punching methods such as the conventional punching, humped bottom punch and two-stage punching by comparing the edge stretchability in terms of HER. Based on the prediction results with the ANN model with multiple input features of sheared edge quality, the following conclusions can be drawn:

1) An ANN model can be an alternative method for predicting the HER of GPa-grade steels with various punching conditions and sheared edge qualities to find nonlinear relationships among the various sheared edge qualities affecting on the edge stretchability.
2) Since physically characterized input parameters are applied to predict HER such as material properties, deformed shape, and material hardening, it is possible to achieve remarkable prediction accuracy with limited amount of data sets.
3) SET test data sets are effective to train nonlinear relationships among the input parameters and output value to improve the prediction accuracy of HER, although it is different edge stretchability test methods in terms of in-plane stretching, unlike HER which is a representative out-of-plane test method.
4) The material hardening parameter is a main influencing factor on edge stretchability, but material properties and the geometrical shape should also be considered to achieve more precise prediction accuracy in which the MAE for predicted value does not exceed 1.5% of HER difference.

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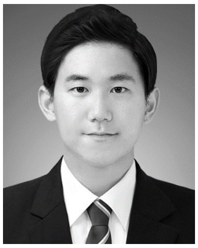

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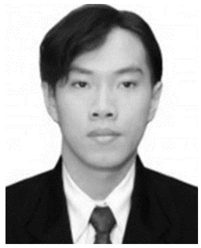

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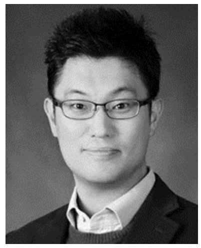

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