

Detection of COVID-19 Using Classification of an X-Ray Image Using a Local Binary Pattern and K-Nearest Neighbors

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Abstract— The recently identified coronavirus pneumonia, which was later given the name COVID-19, is a virus that can be fatal and has affected more than 300,000 individuals around the world. Because there is currently no antiviral therapy or vaccine that has been granted approval by the FDA to cure or prevent this sickness, an automatic method for disease identification is required because of the fast global distribution of this exceedingly contagious and lethal virus. A unique machine learning strategy for automatically detecting this ailment was discovered. Machine learning approaches should be applied in essential jobs in infectious illnesses. As a result, our major aim is to use computer vision algorithms to identify COVID-19 without the need for human interaction. This paper suggested using image processing to classify objects and make early detections using X-ray pictures. Features are extracted for this region using a variety of techniques, including (LBP), (HOG), and use K-Nearest Neighbor algorithm (KNN) for classification, with training percentages of 50%, 60%, 70%, 80%, and 90%. Experiments indicated that using the suggested approach to identify X-ray photos of corona patients, it is feasible to diagnose the disease using X-ray images by training the device on the image data set (about 2,400 photos). The results were tested on the average of the samples taken (random 2000 images) each time and the measurement of multiple training ratios (50%, 60%, 70%, 80%, and 90%). The experimental findings revealed remarkable prediction accuracy in all investigated scenarios, ranging from 85% to 99%.

Keywords— COVID-19, Local Binary Pattern, Histogram of oriented gradient, KNN, X-ray image.

I. INTRODUCTION

COVID-19 is a virus that initially surfaced in the Chinese city of Wuhan in 2019. [1], [2], [3]. Covid-19 illness is a virus family capable of causing acute respiratory syndromes. It spreads quickly from one person to the next all around the world. The virus's outer surface resembles spikes on the crown. It is known as a coronavirus because of its structure [4], [5]. This virus is responsible for several respiratory diseases, including SARS and MERS. [6]. As a result, it results in lung infection injury as well as breathing problems. This condition is extremely dangerous to the public's health. [7]. The overall number of coronavirus cases is about 335,403, with 14,611 deaths and 97,636 recovered. There are now 223,156 affected patients. While 95% of infected individuals are said to survive the sickness in some form, 5% of the remaining patients are said to be in a serious or critical

condition [8]. As the number of persons with COVID-19 illness rises, so does the demand for these patients to undergo intensive care the same time, causing the health system to collapse in all nations throughout the world, including developed ones. With the help of Dr. Joseph Cohen, chest x-rays of 1200 COVID-19 patients and 1200 healthy individuals were gathered from the open source GitHub repository for this study [9]. The KNN method was used to classify X-ray and CT pictures of the main patients in this collection. [10].

II. LITERATURE REVIEW

a significant portion of the global population has been impacted by the respiratory disease COVID-19, which is still having terrible effects. According to a certain study, coronas should be detected as soon as possible.

Jamal N et al [10]. It is proposed that chest X-ray feature extraction be performed using the (LBP), (HOG), and Haralick texture. Six models are built using these features and KNN and SVM classifiers: the LBP-KNN, the HOG-KNN, the Haralick-KNN, the LBP-SVM, the HOG-SVM, and the Haralick. We put the six models through their paces using a five-fold cross-validation training percentage and a dataset size of 500 images. Testing shows a high degree of diagnostic accuracy, between 98.66% and 98.14%. When compared to other models, the LBP-KNN model excels in all four measures of performance: accuracy, sensitivity, specificity, and precision.

Kh. Saddam et al [11]. showed Using a novel implementation of the split-transform-merge principle, the proposed STM-RENet is a block-based convolutional neural network (CNN). Screening X-ray images for COVID-19 infection via channel boosting and learning textural changes. By applying transfer learning to the two additional CNNs, supplemental channels can be generated and added to the primary channels, so increasing their effectiveness. The high sensitivity (97%), specificity (96.53%), and specificity (95%) of the proposed technique suggest that it could be adapted for use in identifying people infected with COVID-19.

K. Sara et al [12]. Using our method, task-specific data pretreatment techniques are no longer necessary, and we

advise using one of several deep convolutional neural networks, including Mobile Net, Dense Net, Exception, Res Net, InceptionV3, VGG Net, and NAS Net, to improve the network's ability to generalize to new data. The effectiveness of the proposed method was tested on the COVID-19 dataset, which contains chest X-ray and CT images. The best result was achieved using the DenseNet121 feature extractor and the Bagging tree classifier, which achieved an accuracy of 99% in classification. Light GBM with ResNet50 feature extractor hybrid had the second-best accuracy among the learners.

S. Ahmet [13]. The study of three distinct COVID-19 data sets required the use of all five stages of the suggested technique, which are as follows: set collection, feature extraction, dimension reduction, and classification. Each level contains a sub-op that must be completed. When applied to datasets 1 (CT), 2 (X-ray), and 3 (CT), respectively, the suggested model has a COVID-19 detection accuracy of 89.41%, 99.02%, and 98.11%. These percentages are in order from lowest to highest. The X-ray data set had an accuracy of 85.96% for determining whether a patient had COVID-19 (+), COVID-19 (-), or pneumonia without COVID-19. The COVID-19 virus may be recognized with a high degree of accuracy in less than a minute by employing methods that involve image processing and learning.

O. Tulin et al [14]. proposed A brand new model for the automatic detection of COVID-19 is presented here, and it makes use of raw X-ray pictures of the chest. The method that has been proposed has the goal of producing accurate diagnostics for both multi-class classification (COVID vs. No-Findings) and binary classification (COVID vs. No-Findings) (COVID vs. No-Findings vs. Pneumonia). Our model produced classification accuracy results of 98.08% and 87.02%, respectively, when it came to binary classifications. As part of the work that we did, the YOLO real-time object recognition system utilized the DarkNet model as its classifier. We employed 17 convolutional layers, and on each layer, we applied a different set of filters.

III. METHODOLOGY

The image classification technique is represented by several steps as seen in fig. 1. the first step in the process of classifying images is the process of extracting features from digital images. These features are based on which a classification model is made. After this step, the design model is built, which depends primarily on the measurement of the distance between the images feature with all the existing and then finding the lowest number found in the values by arranging the values in ascending order and choosing an odd number for these values, and thus there is a number superior to another number. If the number of most of the selected instants is related to a positive example, the class be positive otherwise the instants will be negative. The evaluation of the prediction (testing) is represented by taking a percentage of data for training such as 70%, 80%, or 90%, while the rest is for testing 30%, 20%, and 10% respectively. The class label of features for all data instants are known so, the algorithm tries to find the label of data instants and compare the results with the predefined labels and find the accuracy.

This measurement is used to evaluate the classification model

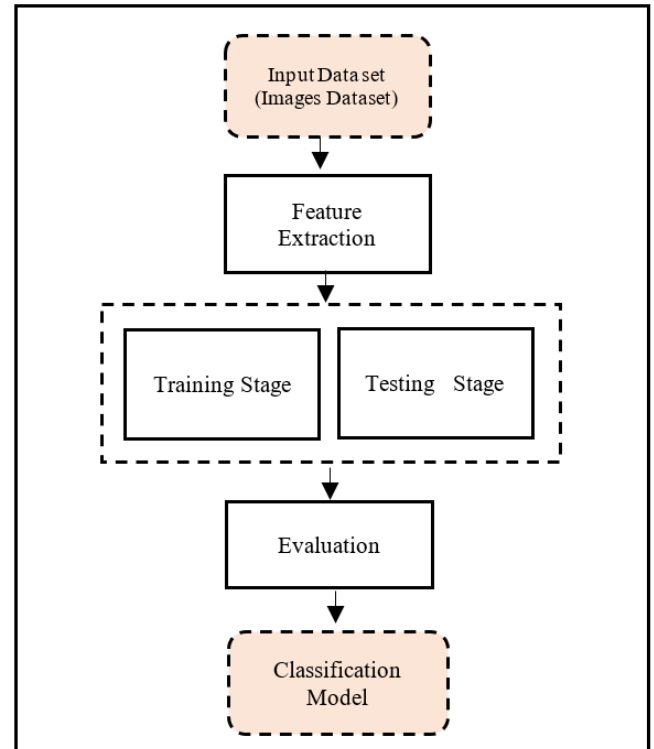


Fig.1. The Block Diagram of Image Classification

IV. IMAGE FEATURE EXTRACTION

Everyone advantages every day from the ability of humans to investigate and categorize objects and environments [15]. We use several classifiers in computer vision, each with its unique set of characteristics and features [16]. Separating the objects comes first in understanding a complex scene, then categorizing the scene. A step in the dimensionality reduction process is feature extraction. Selecting variables and merging them into features makes it easier to extract the best features from large data sets. These functions are easy to comprehend and utilize while accurately reflecting the real data set [17].

A. Local binary pattern (LBP)

In 1994, Ojala was the first to use LBP. It is an easy-to-use and effective feature extractor. LBP's main objective is to extract local features that will improve global characteristics. To identify the pixels of an image and encode the local structure around each pixel, the original LBP operator employed decimal values known as Local Binary Patterns, or LBP codes [18]. The operator assigns a label to each pixel in the (3x3) neighborhood of each pixel by thresholding (Fig. 2). By subtracting the center from the center value of pixels in a (3x3) close-by, and then representing the ensuing number as a binary integer, each pixel is compared to eight of its neighbors [10], [18].

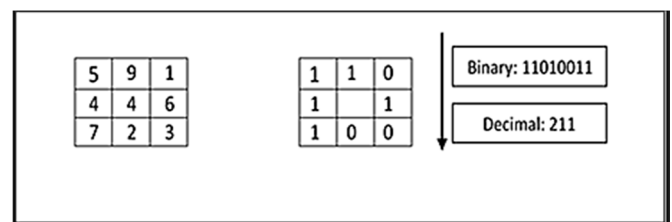


Fig.2. Pixel Neighbors

B. Histogram of oriented gradients (HOG)

It might be challenging to identify people in photos because of their constantly changing appearances and the variety of positions they can take. The first prerequisite is an extensive feature set, especially in congested areas or with poor illumination, that enables it to distinguish itself from the human form. HOG descriptors perform remarkably well compared to other contemporary feature sets [19]. HOGs, a feature descriptor computed by sliding a window detector over an image, have been successfully used for object and pedestrian detection because they represent an object as a single value vector rather than a collection of feature vectors, each of which represents a different region of the image. Each position's HOG descriptor is calculated, and the image's scale is changed to obtain a HOGs feature [20]. This is accomplished by segmenting the window into tiny spatial areas, or cells, with a local histogram of the 1-D gradient directions in each cell. The Oriented Gradient Histogram (HOG) approach for feature extraction combines the picture acquired with the histogram with distinctive characteristics [21].

V. IMAGE CLASSIFICATION USING KNN

KNN is a supervised machine learning algorithm for classification and regression. KNN clusters similar things. Similar objects are nearby. The KNN method depends on this assumption. k-nearest neighbor uses the feature space's closest training samples to classify objects. k-nearest neighbor is a basic machine learning technique. During training, feature vectors and labels from training photos are kept. Unlabeled query points are assigned their nearest neighbor's label during categorization. When categorizing an object, surrounding labels are used as a majority vote. If $k = 1$, the item is in the most similar-shaped class. Two classes require an odd k . Multiclass classification can result in ties even if k is odd. KNN blends similarity with elementary math to calculate graph point distances [22].

A. The KNN Algorithm Stages

The stages that make up the KNN algorithm are as follows: [22].

1. Complete the loading of the information.
2. Determine the desired total number of neighbors and set K to that value.
3. Calculate the difference between the results of your query and the data points that are currently available for the data set.
 - 3.1. Do this for each data point in the data set.
 - 3.2. Include the distance traveled and the index in a collection that has been arranged in ascending order.
4. Arrange the distances and indices in the sorted list from smallest to greatest starting with the distances (in ascending order).
5. Select the first K elements from the collection that have been sorted.
6. Collect the labels that correspond to the K entries that you chose.
7. Calculate an average value for the K labels. if the theory of regression holds.
8. If the classification is necessary, revert to the K label mode.

VI. DISTANCE MEASUREMENT

Machine learning relies heavily on distance metrics. Depending on the type of data, different distance measurements must be chosen and employed. As a result, understanding how to construct and compute a variety of common distance measures, as well as the intuitions behind the resultant scores, is critical [23].

A. The Importance of Distance Measurements

Machine learning commonly makes use of distance measures. Distance is measured in terms of an objective score that summarizes the difference between two objects in the problematic region. Rows of data describing a topic (a person, a car, or a property) or an event are the second most common type of object.

• Hamming Distance

Two binary vectors, binary strings, or bitstrings, are said to have a certain amount of "Hamming distance" if they are statistically different from one another. Each sample might be hot encoded as a bitstring with one bit for each column, such as "red," "green," and "blue" in a column. Each color's values are as follows: [1, 0, 0], [0, 1, 0], and [0, 0, 1].

It is possible to compute the distance between red and green using the total or mean the number of bit inconsistencies in the middle of the two bitstrings. The distance between two locations is known as the Hamming distance. It could be more practical to combine the bit differences across the strings into a single-hot encoded string that will always be either a 0 or a 1 [23].

$$D_H = \sum_{i=1}^N |v_1(i) - v_2(i)| \quad (1)$$

For example, consider bitstrings: If there are a lot of 1 bit, it is more common to calculate the average number of bits different to obtain a hamming distance score between 0 (same) and 1 (different) (all different).

$$D_H = \sum_{i=1}^N |v_1(i) - v_2(i)| / N \quad (2)$$

• Euclidean Distance

The distance between two real-valued vectors is measured using the Euclidean distance. To calculate the Euclidean distance, it is common practice to first normalize or equalize the numerical values in the columns if they are of different scales. If not, rows with large values will skew the distance measure. Euclidean distance is employed by most instance-based learners notwithstanding the availability of additional options. Euclidean distance is found by taking the square root of the sum of the squared differences between the two vectors [23].

$$D_E = \sqrt{\sum_{i=1}^N (v_1(i) - v_2(i))^2} \quad (3)$$

It is usual to skip the formula of square root when doing a distance calculation that will be repeated hundreds of millions of times. The proportions of the generated scores will be the same after this change, and they may continue to be utilized

in a machine learning algorithm to choose instances that are the most comparable.

$$D_E = \sum_{i=1}^N (v_1(i) - v_2(i))^2 \quad (4)$$

The L2 vector norm is used in this calculation, which is analogous to the error squared and, after taking the square root, the root sum squared error.

- Manhattan Distance

When comparing two vectors with real values, the Manhattan distance is used as a metric. It's a measure of travel commonly used in the city, and it goes by several names. When describing objects on a regular grid, such as a chessboard or city blocks, it may be more useful to use vectors. Taxicab distance measures the shortest route a taxicab can take across a city's blocks, as represented by the grid's coordinates.

It's possible that calculating the Manhattan distance between two vectors in an integer feature space makes more sense than calculating the Euclidean distance between them. Simply adding the two vectors' absolute values together is all that is required to calculate the Manhattan distance [23].

$$D_M = \sum_{i=1}^N |v_1(i) - v_2(i)| \quad (5)$$

The Manhattan distance is related to the L1 vector norm, the total absolute error, and the mean absolute error.

- Minkowski Distance

Minkowski distance is used to compute the distance between two vectors with real values. It's an extension of the Euclidean and Manhattan distance measurements that incorporates an "order" or "p" parameter that allows for the computation of numerous distance measures [23].

The Minkowski distance is determined in the following way:

$$Du = \sum_{i=1}^N |(v_1(i) - v_2(i))^p| \cdot 1 / P \quad (6)$$

For the order parameter, write "p."

In the simplest case, where $p = 1$, the result is identical to the Manhattan distance. In the case where $p = 2$, the distance is the same as the one calculated using the Euclidean method. Distancing from Manhattan: $p=1$, Euclidean Distance: $p=2$. The intermediate values are a good compromise between the two extreme values.

VII. EXPERIMENTAL RESULTS

The extracted features are used in the classification process and are used for building the classification model for COVID19 disease. The proposed method was applied to the dataset that contained about 2400 x-ray images.

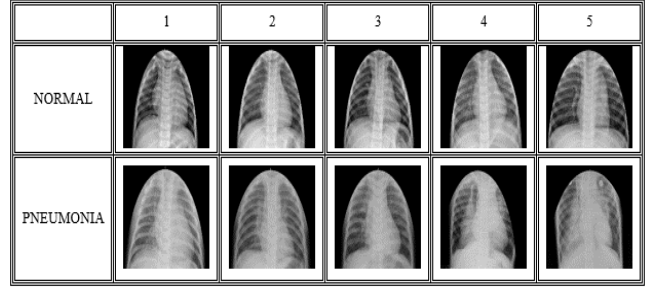


Fig.3. Image Samples of Normal &Pneumonia X-Ray Chests.

For the evaluation of the classification results, the KNN was used. The results were tested on the average of the samples taken (random 2000 images) each time and the measurement of multiple training ratios (50%, 60%, 70%, 80%, and 90%). Tables 1 and 2 show the confusion matrix metrics for LBP and HOG features with KNN classification, respectively. These metrics include accuracy, error rate, sensitivity, false positive rate, specificity, precision, and prevalence.

Table 1: LBP-KNN Classification Result

Training rate	Accuracy	Error Rate	Sensitivity	False Pos. Rate	Specificity	Precision	Prevalence
50%	0.8341	0.1659	0.8998	0.0000	1.0000	1.0000	0.7942
60%	0.8408	0.1592	0.9022	0.0000	1.0000	1.0000	0.8014
70%	0.8456	0.1544	0.8979	0.0000	1.0000	1.0000	0.8185
80%	0.8490	0.1510	0.9140	0.0000	1.0000	1.0000	0.8090
90%	0.8635	0.1365	0.9304	0.0000	1.0000	1.0000	0.8217

Table 2: HOG-KNN Classification Result

Training rate	Accuracy	Error Rate	Sensitivity	False Pos. Rate	Specificity	Precision	Prevalence
50%	0.7838	0.2162	0.8184	0.0000	1.0000	1.0000	0.7597
60%	0.7945	0.2055	0.8279	0.0000	1.0000	1.0000	0.7729
70%	0.7910	0.2090	0.8200	0.0000	1.0000	1.0000	0.7821
80%	0.7965	0.2035	0.8254	0.0000	1.0000	1.0000	0.7730
90%	0.8160	0.1840	0.8295	0.0000	1.0000	1.0000	0.8041

VIII. CONCLUSION

In this Paper training a device on a dataset of X-ray images of people with COVID-19, the condition can be diagnosed using imaging alone. Taken from the Kaggle website is a group of images, some of which are X-rays of people who are well and others who have various diseases (about 5,000 images). There are approximately 2,400 images that are evaluated, and the results are obtained from a different group of random samples chosen from the total number of images for the number of iterations using a variety of training sizes ranging from 50% to 90%. All the calculations that were performed, including those for accuracy, error rate, sensitivity, false positive rate, specificity, precision, prevalence, and incidence, came out accurate. LBP and HOG are two examples of approaches that can be used for feature extraction.

REFERENCES

- [1] H. Lau, V. Khosrawipour, P. Kocbach, A. Mikolajczyk, H. Ichii, J. Schubert and J. Bania, T. Khosrawipour, "Internationally lost COVID-19 cases." *Journal of Microbiology, Immunology and Infection* *V. 53, I. 3*, pp. 454-458, June 2020.
- [2] J.-f. Zhang, K. Yan, H.-h. Ye, J. Lin, J.-j. Zheng and T. Cai, "SARS-CoV-2 turned positive in a discharged patient with COVID-19 arouses concern regarding the present standard for discharge." *Int. J. Infect. Dis.*, 97: pp.212-214, Aug 2020.
- [3] G. Lippi, M. Plebani and B.M. Henry, "Thrombocytopenia is associated with severe coronavirus disease 2019 (COVID-19) infections: a meta-analysis." *Clin. Chim. Acta.* 506:145-148, Jul 2020.
- [4] H.A. Rothan, S.N. Byrareddy, "The epidemiology and pathogenesis of coronavirus disease (COVID-19) outbreak." *J. Autoimmun.* 109:102433, May 2020.
- [5] S. Chavez, B. Long, A. Koyfman, S.Y. Liang." Coronavirus Disease (COVID-19): a primer for emergency physicians." *Am. J. Emerg. Med.* 44:220-229, Jun 2020.
- [6] A.J. Rodriguez-Morales, J.A. Cardona-Ospina, E. Gutiérrez-Ocampo, R. Villamizar-Peña, Y. Holguin-Rivera, J.P. Escalera-Antezana, L.E. Alvarado-Arnez, D.K. Bonilla-Aldana, C. Franco-Paredes, A.F. Henao-Martinez," Clinical, laboratory and imaging features of COVID-19: a systematic review and meta-analysis." *Trav. Med. Infect. Dis.* 34:101623, Apr 2020.
- [7] A. Cortegiani, G. Ingoglia, M. Ippolito, A. Giarratano, S. Einav "A systematic review on the efficacy and safety of chloroquine for the treatment of COVID-19". *J. Crit. Care.* 57:279-283, Jun 2020.
- [8] A. Narin, C. Kaya, Z. Pamuk. "Automatic Detection of Coronavirus Disease (COVID-19) Using X-ray Images and Deep Convolutional Neural Networks". *Pattern Analysis and Applications*, 24:1207–1220, May 2021.
- [9] W. Chen and Q. Cao, "Feature Points Extraction and Matching Based on Improved Surf Algorithm." 2018 IEEE International Conference on Mechatronics and Automation (ICMA), pp. 1194-1198, 10.1109/ICMA.2018.8484336 Jun 2018.
- [10] J. N. Hasoon, A. H. Fadel, R. S. Hameed, S. A. Mostafa, B. A. Khalaf, M. A. Mohammed and J. Nedoma, "COVID-19 anomaly detection and classification method based on supervised machine learning of chest X-ray images." *Results phys.* ;31:105045, Dec 2021.
- [11] S. H. Khan, A. Sohail, A. Khan and Y. S. Lee, "COVID-19 Detection in Chest X-ray Images Using a New Channel Boosted CNN." *Diagnostics*, 12, 267, 2022.
- [12] S. H. Kassania, P. H. Kassania, M. J. Wesolowskic, K. A. Schneidera and R. Detersa , "Automatic Detection of Coronavirus Disease (COVID-19) in X-ray and CT Images: A Machine Learning Based Approach." *PMC*, 5. doi: [10.1016/j.bbe.2021.05.013](https://doi.org/10.1016/j.bbe.2021.05.013), Jun 2021.
- [13] A. Saygaili, "A new approach for computer-aided detection of coronavirus (COVID-19) from CT and X-ray images using machine learning methods." *PMC*, ; doi: [10.1016/j.asoc.2021.107323](https://doi.org/10.1016/j.asoc.2021.107323), Mar 2021.
- [14] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim and U. R. Acharya, "Automated detection of COVID-19 cases using deep neural networks with X-ray images." *PMC*, ; doi: [10.1016/j.combiomed.2020.103792](https://doi.org/10.1016/j.combiomed.2020.103792), Apr 2020.
- [15] S. Thorpe, D. Fize and C. Marlot, "Speed of processing in the human visual system." *Nature*, 381, pp. 520–522, June 1996.
- [16] A. Treisman and G. Gelade, "A feature integration theory of attention." *Cognitive Psychology*, 12, pp. 97–136, 1980.
- [17] "Feature Extraction." 15 01 2022 Available: <https://deeptai.org/machine-learning-glossary-and-terms/feature-extraction>.
- [18] D. Huang, C. Shan, M. Ardabilian, Y. Wang, L. Chen, "Local Binary Patterns and Its Application to Facial Image Analysis: A Survey." *Hal open science*, pp. 1-17, Mar 2017.
- [19] N. Dalal and B. Triggs, "Histograms of Oriented Gradients for Human Detection." *Hal open science*, pp. 886-893, Dec 2010.
- [20] C. Rahmad et al "Comparison of Viola-Jones Haar Cascade Classifier and Histogram of Oriented Gradients (HOG) for face detection." *IOP Conf. Ser.: Mater. Sci. Eng.* 732 012038, 2020.
- [21] Z. Julius, R. Vidas, M. Rytis, D. Robertas, "Recognition of basketball referee signals from videos using Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM)." *Procedia Computer Science*, pp. 953–960, Dec 2018.
- [22] "Machine Learning Basics with the K-Nearest Neighbors Algorithm." 15 01 2022 Available: <https://towardsdatascience.com/machine-learning-basics-with-the-k-nearest-neighbors-algorithm-6a6e71d01761>.
- [23] "4 Distance Measures for Machine Learning." 15 01 2022 Available: <https://machinelearningmastery.com/distance-measures-for-machine-learning/>
M. Young, *The Technical Writer's Handbook*. Mill Valley, CA: University Science, 1989.