

Original Research Article

Artificial Neural Network versus k-Nearest Neighbour Classification of Ischaemic Stroke Lesion Age Using Non-Contrast CT Texture Features

Ugochukwu Celestine Opara^{1,2*}, Anthony Chukwuka Ugwu¹, Christopher Chukwuemeka Ohagwu¹, Bestman Izuchukwu Oriaku⁵, Emmanuel Ayuba Buba⁶, Emeka Chukwumanya Umeh³, Stanley Olisa Nwefuru⁷, Uche Andrew George⁴, Victor Kelechi Nwodo¹, Emeka Emmanuel Ezugwu¹, Lawrence Daberechi Ifesie¹, Sharonrose Ogochukwu Nwadike¹

¹Department of Radiography and Radiological Science, Nnamdi Azikiwe University, Awka, Anambra State, Nigeria

²CT/MRI Department, Barnsley Hospital NHS Foundation Trust, United Kingdom

³CT Department, Humber Health Partnership, Hull University Teaching NHS Trust, Hull, United Kingdom

⁴Department of Ultrasound, Northern Lincolnshire and Goole NHS Foundation Trust, Grimsby, United Kingdom

⁵Department of Interventional Radiology, University of Liverpool NHS Foundation Trust, United Kingdom

⁶MRI Department, Nottingham University Hospital NHS Trust, Nottingham, United Kingdom

⁷MRI Department, North East Lincolnshire and Goole NHS Foundation Trust, Grimsby, United Kingdom

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Abstract: Background: Accurate estimation of the age of an ischaemic stroke lesion is clinically important because therapeutic decisions are strongly dependent on time from stroke onset. Non-contrast computed tomography (NCCT) remains the most accessible first-line neuroimaging modality for stroke assessment particularly in resource-constrained settings. However, temporal changes in infarct appearance may be subtle and difficult to characterise consistently by visual assessment alone; quantitative texture analysis combined with machine learning may provide an objective approach to automated lesion-age classification. This study compared the performance of an Artificial Neural Network (ANN) and a k-Nearest Neighbour (k-NN) classifier for classifying ischaemic stroke lesion age using statistical texture features extracted from NCCT images. **Methods:** A prospective cross-sectional purposive study was conducted among 197 patients with clinically diagnosed ischaemic stroke who underwent NCCT at three diagnostic centres in Nigeria. Following radiological confirmation, 316 regions of interest (ROIs) comprising 158 normal brain tissue ROIs, 58 acute lesions, 50 subacute lesions and 50 chronic lesions were analysed. Four classes of statistical texture descriptors—Histogram, Grey-Level Co-occurrence Matrix (GLCM/COM), Run-Length Matrix (RLM) and Absolute Gradient were extracted from the selected ROIs. Feature reduction was performed using the Fisher coefficient and the most discriminating parameters from each texture class were used for classification. A multilayer feed-forward ANN and a k-NN classifier with $k = 1$ were implemented using scikit-learn. The dataset was divided into 80% training and 20% testing subsets using stratified sampling. Classification performance was assessed using sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), F1-score, Cohen's kappa, and area under the receiver operating characteristic curve (AUROC). **Results:** The classifiers demonstrated substantially different performance depending on the texture descriptor used. Histogram features produced the strongest overall classification performance. The ANN achieved a Cohen's kappa of 0.718, while k-NN achieved a higher kappa of 0.812. Using Histogram features, the ANN achieved AUROCC values of 1.000 for normal tissue, 0.926 for acute lesions, 0.872 for subacute lesions, and 0.980 for chronic lesions. Corresponding k-NN AUROCC values were 1.000, 0.827, 0.781, and 0.941, respectively. k-NN demonstrated higher sensitivity for acute lesions (0.750 versus 0.667) and subacute lesions (0.600 versus 0.400), while ANN demonstrated higher AUROCC values for acute, subacute, and chronic lesions. RLM features favoured

ANN, which achieved AUROC values of 0.891, 0.922 and 0.924 for acute, chronic and subacute lesions, respectively, compared with 0.785, 0.722 and 0.763 for k-NN. Conversely, both classifiers performed poorly with absolute gradient features, particularly for chronic lesions, with ANN producing an AUROC of 0.520 and k-NN 0.485. GLCM features produced moderate performance, with ANN and k-NN achieving overall Cohen's kappa values of 0.273 and 0.284, respectively. **Conclusion:** Both ANN and k-NN demonstrated the ability to classify ischaemic stroke tissue chronological stage using NCCT-derived texture features, as their performance was strongly dependent on the texture descriptor. Histogram features were the most informative and produced the highest overall classification performance. k-NN achieved the highest overall agreement with the reference classification when Histogram features were used, whereas ANN demonstrated greater discriminative performance across several individual lesion stages and greater robustness with RLM features. These findings support the potential of quantitative NCCT texture analysis as a computer-aided approach to ischaemic stroke lesion-age classification, particularly in settings where advanced neuroimaging is limited.

Keywords: Ischaemic Stroke, Non-Contrast Computed Tomography, Texture Analysis, Radiomics, Artificial Neural Network, K-Nearest Neighbour, Lesion Age, Machine Learning, Nigeria.

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INTRODUCTION

According to Campbell, De Silva and Macleod (2019), ischaemic stroke is a major neurological emergency caused by an interruption of cerebral blood flow resulting in neuronal dysfunction and when sufficiently prolonged leads to irreversible infarction. The clinical consequences of stroke are strongly influenced by the duration of cerebral ischaemia and the amount of tissue that remains potentially salvageable. Consequently, the rapid determination of stroke onset and lesion status is central to acute stroke management (Campbell *et al.*, 2019). The time-dependent nature of acute ischaemic stroke treatment has made lesion-age determination an important clinical problem. Intravenous thrombolysis is generally most beneficial when administered within a narrow therapeutic window (Hacke *et al.*, 2008). Meanwhile, mechanical thrombectomy may benefit selected patients within early and extended time windows (Powers, Rabinstein, and Ackerson, 2018). The present study therefore emphasised the importance of determining whether a lesion is acute, subacute or chronic when the precise time of stroke onset is uncertain.

In line with Schneider and Patel (2002), non-contrast computed tomography (NCCT) is routinely used as the initial imaging investigation in suspected acute stroke because it is rapid, relatively inexpensive and widely available. Jäger (2000) stated that NCCT is particularly valuable in resource-constrained healthcare environments where MRI, CT perfusion and other advanced neuroimaging techniques may not be readily accessible. However, early ischaemic changes may be subtle on conventional NCCT and lesion appearance evolves progressively over time (Boulouis *et al.*, 2016).

This creates a challenge when visual assessment alone is used to estimate the chronological stage of an infarct.

According to Zwanenburg *et al.*, (2020), texture analysis provides a quantitative approach to this problem. Rather than relying exclusively on visual recognition, texture analysis mathematically characterises the distribution and spatial relationships of grey-level intensities within a defined region of interest (ROI). The present study investigated four major statistical texture classes: Histogram, Grey-level co-occurrence matrix (GLCM), Run-length matrix (RLM) and Absolute Gradient features. Lerski (1979) stated that Histogram features characterise the distribution of grey-level intensities within an ROI. GLCM features quantify relationships between neighbouring grey levels and provide measures of contrast, homogeneity and spatial dependence. RLM features describe consecutive runs of similar grey levels whereas Absolute Gradient descriptors characterise local intensity changes. These complementary descriptors provide different representations of tissue characteristics.

Machine learning offers an opportunity to convert these quantitative descriptors into automated classification systems. Two supervised approaches investigated in the present study were a multilayer feed-forward Artificial Neural Network (ANN) and a k-Nearest Neighbour (k-NN) classifier. The ANN learns complex relationships between input features and predefined tissue classes through a network of interconnected computational units. In contrast, k-NN classifies an observation according to its similarity to previously classified observations and is a non-parametric approach (Duda, Hart and Stork, 2001). According to the comparative evaluation by Pedregosa,

Varoquaux, and Gramfort (2011), it is important to evaluate these two approaches because superior performance cannot be assumed based on the choice of algorithm alone. The predictive value of a machine-learning model depends on the characteristics of the input data, the discriminative capacity of the features and the structure of the classification problem. Previous work has demonstrated the potential of computer-assisted analysis of CT images for the detection and classification of stroke.

The present study therefore aimed to compare ANN and k-NN for the automated classification of ischaemic stroke lesion age using statistical texture features derived from routine NCCT images.

Study Objective

The specific objective was to compare the performance of ANN and k-NN classifiers in distinguishing normal brain tissue, acute ischaemic lesions, subacute ischaemic lesions and chronic ischaemic lesions using Histogram, GLCM, RLM, and absolute gradient features extracted from NCCT images.

Research Hypothesis

The study tested the hypothesis that ischaemic stroke lesions cannot be reliably identified and classified according to chronological stage using statistical texture parameters and machine-learning algorithms.

2. MATERIALS AND METHODS

Study Design and Population

A prospective cross-sectional purposive study was undertaken among patients clinically diagnosed with ischaemic stroke who underwent NCCT examination of the brain. A total of 197 patients were included in the study. The cohort had a mean age of 61.3 ± 12.6 years, an age range of 27–90 years and 56.3% of participants were aged 60 years or older. The mean interval between reported stroke onset and CT examination was $77.5 \pm$

34.8 hours. The patients were recruited from three diagnostic centres in Nigeria, namely: Image Diagnostics, Port Harcourt, Rivers State, St Charles Diagnostics, Awka, Anambra State; and Image Diagnostics, Owerri, Imo State.

CT Image Acquisition

NCCT examinations were performed using multidetector CT scanners available at the participating centres. The parent study used among other equipment, a GE Revolution ACT 32 slice CT scanner and a 64-slice Siemens SOMATOM CT scanner using a 512×512 reconstruction matrix.

Image Normalisation

Because CT examinations were acquired on different scanner systems and imaging settings, image normalisation was performed before texture analysis. The present study employed a ± 3 sigma normalisation method to reduce differences in grey-level ranges attributable to scanner and acquisition variability. This standardisation is important because differences in acquisition and reconstruction parameters can influence quantitative imaging biomarkers and radiomic measurements (Zwanenburg *et al.*, 2020).

Texture Feature Extraction

Four statistical texture classes were extracted: Histogram, GLCM, RLM and Absolute Gradient. Histogram-based descriptors represent first-order intensity distributions whereas GLCM and RLM features provide higher-order information concerning spatial relationships and grey-level organisation. For GLCM analysis, inter-pixel distances of 1–5 pixels were evaluated at four orientations: 0° , 45° , 90° , and 135° resulting in 20 matrices for each ROI. Texture extraction was performed using MaZda version 4.6.2. MaZda has been used as a platform for computer-based texture analysis of medical images.

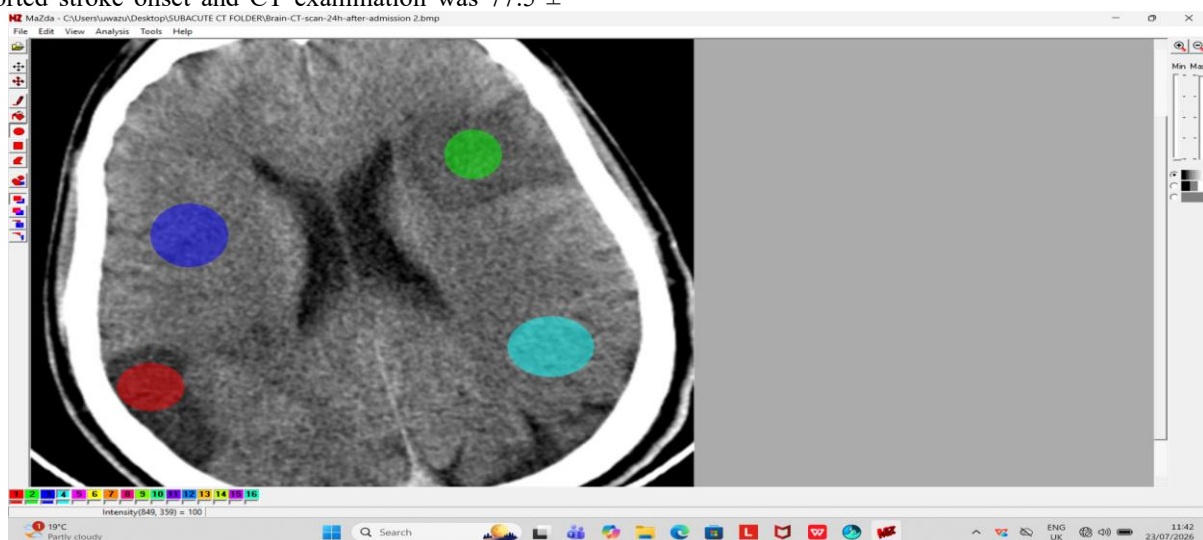


Fig 1: ROI 1 (red) and ROI 2 (green) are on ischaemic tissues on the right and left cerebral hemispheres. ROIs 3 and 4 (blue and sky blue) are on normal tissues on right and right cerebral hemispheres

Machine-Learning Classification

Two supervised machine-learning algorithms were evaluated: Artificial Neural Network and k-Nearest Neighbour. The ANN was implemented using the scikit-learn Python library, while the k-Nearest Neighbour classifier was implemented with the study's specified k parameter. The present study reports $k = 1$ for the k-NN analysis; this value is consistent with the one-nearest-neighbour approach in which each test observation is assigned according to the closest training observation (Gurney, 1992). Classification performance was evaluated using diagnostic and agreement measures, including sensitivity, specificity, predictive values, F1-

score, Cohen's kappa and area under the receiver operating characteristic curve (AUROCC).

3. RESULTS

3.1 Performance of Statistical Texture Features

All four texture classes demonstrated statistically significant differences between normal, acute, subacute and chronic tissues ($p < 0.001$). Histogram features demonstrated the greatest discriminatory power, followed by RLM, GLCM and Absolute Gradient features.

Table 1: showing the statistical performance of the texture features

Texture class	Range of p -values	Relative performance
Histogram	$9.64 \times 10^{-56} - 1.62 \times 10^{-54}$	Highest
RLM	$2.18 \times 10^{-30} - 6.68 \times 10^{-30}$	High
GLCM	$1.51 \times 10^{-23} - 8.50 \times 10^{-28}$	Moderate-high
Absolute Gradient	$1.45 \times 10^{-10} - 3.26 \times 10^{-17}$	Lowest

Histogram parameters produced the clearest separation of the tissue groups in three-dimensional feature-space analysis.

3.2 Overall classification performance

Histogram features produced the strongest overall classification performance. k-NN achieved the

highest overall Cohen's Kappa (0.812), compared with 0.718 for ANN.

Table 2: showing the classification performance of k-NN and ANN

Texture feature	ANN Kappa	k-NN Kappa	Best performer
GLCM	0.273	0.284	k-NN
Absolute Gradient	0.193	0.219	k-NN
Histogram	0.718	0.812	k-NN
RLM	0.547	0.503	ANN

3.3 ROC Curve Analysis

ROC analysis demonstrated that Histogram features produced the highest discriminatory performance for both classifiers.

For the ANN, the ROC curves therefore demonstrated excellent discrimination for normal and

chronic tissue and good-to-excellent discrimination for acute and subacute lesions.

k-NN also demonstrated excellent discrimination for normal and chronic tissue, although its discrimination of acute and subacute lesions was lower than that achieved by ANN.

Table 3: Histogram-based ROC performance

Tissue category	ANN AUROCC	k-NN AUROCC	Interpretation
Normal	1.000	1.000	Perfect discrimination
Chronic	0.980	0.941	Excellent
Acute	0.926	0.827	Excellent/good
Subacute	0.872	0.781	Good/fair-good

These findings indicate that the Histogram features provided substantially better separation of the tissue categories than the other texture classes. Both models achieved 100% sensitivity and specificity for normal tissue. For chronic lesions, ANN achieved 80.0% sensitivity and 96.3% specificity, while k-NN achieved 90.0% sensitivity and 98.1% specificity. ANN demonstrated stronger performance with RLM features for subacute lesions, achieving an AUROCC of 0.924, compared with 0.763 for k-NN. Absolute Gradient features produced the poorest performance, particularly

for chronic lesions, where ANN sensitivity was 0% and k-NN sensitivity was 10%.

4. DISCUSSION

The principal finding of this study is that the performance of machine-learning algorithms for ischaemic stroke lesion-age classification was strongly dependent on the texture descriptor used. The most important finding was the superiority of Histogram features. The high performance of Histogram features is biologically plausible, based on the fact that the

evolution of an ischaemic infarct is accompanied by constant changes in tissue attenuation. For example, attenuation decreased from 123.59 ± 10.96 in normal tissue to 86.74 ± 13.27 in acute lesions, 77.65 ± 12.55 in subacute lesions, and 50.46 ± 10.73 in chronic lesions. These findings are consistent with the observations of Ohagwu and Agwu (2018) and with the established evolution of CT attenuation following cerebral infarction, in which tissue hypoattenuation becomes progressively more conspicuous as infarction evolves [5–7]. The quantitative findings also support the concept that NCCT contains information beyond simple visual recognition and that this information may be exploited computationally.

ANN Versus k-NN Using Histogram Features

The k-NN classifier achieved the higher overall Cohen's kappa (0.812 versus 0.718), suggesting greater overall agreement with the reference classification. However, ANN produced higher AUROC values for acute, subacute and chronic lesions. This illustrates that overall agreement and class-specific discrimination provide complementary information when evaluating machine-learning classifiers. The findings also demonstrate that a simpler non-parametric classifier can perform strongly when the input feature space contains highly discriminative information. Histogram features are first-order descriptors and may capture the substantial attenuation differences associated with infarct maturation without requiring more complex modelling of spatial relationships (Haralick, Shanmugam, and Dinstein, 1973).

ANN Performance with RLM Features

The ANN demonstrated a particularly strong advantage when RLM features were used. For subacute lesions, the ANN achieved an AUROC of 0.924 compared with 0.763 for k-NN. This suggests that the non-linear mapping capabilities of a multilayer neural network may have been advantageous for the spatially complex information represented by run-length descriptors. In line with the study by Galloway (1975), RLM features quantify the distribution of consecutive pixels with similar grey-level values and may therefore provide information that is not captured adequately by first-order intensity measures alone. The ability of ANN to model interactions between multiple features may have contributed to its stronger performance with these descriptors.

Limitations of k-NN with Non-Histogram Features

k-NN showed relatively weak performance with GLCM and Absolute Gradient features. The k-NN approach used $k = 1$, meaning that each test observation was assigned according to its nearest training observation. Although this approach is simple and computationally efficient, its performance can be sensitive to feature scaling, noise, class distribution and the local geometry of the feature space as this also agrees with a research by Duda, Hart and Stork in 2000. The

relatively weaker performance with some higher-order texture descriptors suggests that nearest-neighbour similarity may not adequately capture complex non-linear relationships between texture features and lesion age.

GLCM Features

GLCM features demonstrated moderate performance. ANN achieved an AUROC of 0.856 for chronic lesions and 0.820 for subacute lesions while k-NN achieved 0.631 and 0.517 respectively. The present study found that GLCM contrast decreased with infarct maturation while inverse difference moment increased suggesting that acute infarcts were more heterogeneous and chronic infarcts were more homogeneous. These observations are consistent with the theoretical basis of GLCM analysis in which contrast reflects local grey-level variation while measures such as inverse difference moment capture local homogeneity. This, changes in tissue structure during infarct evolution may be reflected in alterations of spatial grey-level relationships as these findings are in line with the study conducted by Nogueira in 2018.

RLM Features and Subacute Lesions

RLM features were particularly effective for identifying subacute lesions with ANN. The AUROC of 0.924 was one of the highest values obtained in the entire study. The parent study reported substantial changes in run-length parameters during infarct evolution including increases in grey-level non-uniformity values in subacute lesions. The strong performance of ANN with RLM features suggests that combinations of spatial texture descriptors may contain information about infarct evolution that is difficult to exploit through simple distance-based classification. This supports the use of machine-learning methods capable of learning non-linear relationships between multiple quantitative imaging variables as this aligns with the previous research findings by Pedregosa, Varoquaux and Gramfort in 2011.

Clinical and Translational Implications

The findings have potential relevance to clinical environments in which NCCT is substantially more accessible than MRI or CT perfusion. A computer-aided system capable of extracting quantitative information from routine NCCT could potentially assist clinicians in estimating the chronological stage of an infarct when the exact onset time is uncertain. This is particularly relevant in patients with unwitnessed stroke, delayed presentation or incomplete clinical histories. The present study emphasised that advanced modalities may be inaccessible or expensive in the Nigerian healthcare context where stroke care continues to face resource and infrastructure constraints (Komolafe *et al.*, 2007). The potential clinical value of such systems should nevertheless be interpreted cautiously. Texture-based classification should be regarded as an adjunct to clinical assessment and conventional imaging interpretation

rather than a replacement for established stroke-imaging protocols. Standardisation of acquisition, segmentation and feature extraction would also be necessary before deployment across multiple institutions as this also corroborates with the findings of Lambin *et al.*, in 2012.

Among the tested approaches, Histogram-based models appear particularly attractive because first-order Histogram parameters are computationally simpler than more complex higher-order radiomic representations. Radiomics broadly seeks to convert medical images into quantitative data that can support diagnosis, prognosis and treatment decision-making as stated previously in a 2016 study by Gillies, Kinahan and Hricak.

Strengths of the Study

First, the study directly compares two fundamentally different supervised-learning approaches using the same imaging dataset and texture descriptors. Second, it evaluates four complementary statistical texture classes rather than relying on a single feature family. Third, classification performance was assessed using multiple diagnostic measures, including sensitivity, specificity, predictive values, F1-score, Cohen's kappa and AUROC. The use of multiple texture families is particularly important because different descriptors capture different properties of image appearance. Histogram features characterise intensity distribution, GLCM features capture neighbouring-pixel relationships, RLM features describe grey-level runs and Absolute Gradient features quantify local intensity variation.

Limitations

Scanner and Acquisition Variability

The images were acquired using different CT scanners and protocols across the participating centres. Although image normalisation and harmonisation were performed, differences in scanner hardware, reconstruction methods, slice thickness and acquisition parameters may affect texture measurements. Such variability is a recognised challenge in quantitative imaging and radiomics research making standardisation and reproducibility essential for clinical translation.

Additional limitations include the use of a relatively modest single-cohort dataset and the potential for model performance to be influenced by the specific characteristics of the study population. Consequently, the reported performance measures should not automatically be generalised to other populations or imaging environments without independent external validation.

Recommendations for Future Research

Future research should focus on broader radiomic feature extraction including shape, Grey-Level Size Zone Matrix (GLSZM), Grey-Level Dependence Matrix (GLDM), Neighbouring Grey-Tone Difference Matrix (NGTDM) and wavelet-based features. The parent study specifically recommends broader

radiomics, advanced artificial intelligence, automated segmentation and longitudinal patient tracking as important directions for further research. Future studies should also investigate larger multicentre datasets and independent external validation. Harmonisation of CT acquisition parameters and standardisation of segmentation and feature-extraction procedures will be important for improving reproducibility. Automated lesion segmentation could further reduce observer variability and facilitate integration into clinical workflows.

Comparative evaluation of additional machine-learning and deep-learning algorithms may also determine whether the observed performance can be improved. Prospective validation would ultimately be required to establish whether automated lesion-age classification can provide clinically meaningful information for patients presenting with uncertain or unwitnessed stroke onset.

5. CONCLUSION

This study demonstrates that both Artificial Neural Network and k-Nearest Neighbour classifiers can extract clinically relevant temporal information from statistical texture features derived from routine NCCT images of ischaemic stroke. However, classifier performance was strongly dependent on the texture descriptor. Histogram features were clearly the most effective overall producing Cohen's kappa values of 0.718 for ANN and 0.812 for k-NN. ANN also demonstrated particular strength with RLM features achieving an AUROC of 0.924 for subacute lesions compared with 0.763 for k-NN. The findings indicate that routine NCCT contains quantitative information reflecting the temporal evolution of ischaemic infarction that can be exploited computationally.

The results support further investigation of texture analysis and machine-learning approaches as potential computer-aided tools for estimating ischaemic stroke lesion age, particularly in resource-constrained settings where NCCT is considerably more accessible than advanced neuroimaging modalities. However, external validation, imaging standardisation, automated segmentation and prospective clinical evaluation are required before such approaches can be incorporated into routine clinical practice.

Author Contributions

This research work was carried out in collaboration with other authors. Author Ugochukwu Celestine Opara designed the study, performed the statistical analysis, wrote the protocol and first drafted the manuscript. Author Ugwu A.C. and Ohagwu C.C supervised the entire study. Both read and approved the final manuscript and others have contributed to the success of the work to this stage.

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