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Neuroblastoma Histology: Computer-Assisted Isolation of Cancerous Cells Image segmentation Techniques

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Abstract

Neuroblastoma is the third most prevalent form of childhood cancer among children. It is a malignancy of the adrenal glands, which are located above the kidney. It typically affects specific areas, including the stomach, chest, neck, pelvis, and bones. On average, neuroblastoma cancer is detected in children between the ages of 1 and 2. Certain imaging methods can reveal its presence. Imaging is an important part of the Neuroblastoma diagnostic, staging, therapy planning, response evaluation, and monitoring processes. Cell morphology, as observed in H&E-stained pictures, plays a role in the current prognostic categorization of this disease (Hematoxylin and eosin). The primary objective is to use colour segmentation, cell extraction, boundarization, and major minor axis recognition to identify cancer cells in H&E-stained images.

Keywords: Staining method (H&E), Neuroblastoma, Segmentation, Image analysis, Machine learning, Medical image processing.

Introduction

One type of cancer, known as neuroblastoma, affects the adrenal glands, which are located above the kidney. Typically, it impacts specific areas including the stomach, chest, neck, pelvis, and bones. The most common age group to be impacted by this type of cancer is children. Neuroblastoma is the most typical form of cancer in youngsters (found usually in children younger than 1 year old). There are about 700–800 new cases of neuroblastoma diagnosed annually in the United States^[1]

This diagnosis rate has been stable for a long time. Neuroblastoma cancer typically affects children between the ages of 1 and 2. In a limited number of cases, it can be detected even before birth by ultrasonography. In around 9 out of 10 instances, a diagnosis is made. Rarely affects kids younger than 10 years, usually because of better hygiene. A child's median age at diagnosis is 22 months. Six percent of all cases of juvenile cancer in the United States are caused by neuroblastoma. In the present grading system for patients with this disease, pathologists must identify certain morphological characteristics by microscopic examination of tumour samples. Neuroblasts are immature, tiny, spherical, undifferentiated sympathetic cells with limited cytoplasm, dark nuclei, and few undetectable nucleoli^[1] Homer-Wright rosettes (a form of pseudorosette in which differentiated tumour cells surround the neuropil) are sporadic cellular groupings that are typical of Neuroblastoma. It is diagnosed using

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the elevated urinary levels of catecholamines and the characteristic histopathologic characteristics.

Neuroblastic tumours are frequently stratified into risk groups according to histological findings and given a prognosis using the Shimada classification (Fig 1) and The Paediatric Oncology Group (POG) classification. According to POG, NBL, which accounts for 50% of the 'differentiated,' can be further classified into the most immature form, the undifferentiated, and the most mature form, the differentiated. It considers histological and morphologic factors, as well as the patient's age at the time of diagnosis. A cancer's 'favourable' or 'unfavourable' form is determined by a combination of patient age, mitosis-karyokinesis index (MKI), cellular and stromal maturity.^[2]

As shown in Figure 1, NBL is classified as having either favourable or unfavourable histology.

Favourable Histological Features: Children aged 1.5 to 5 years with a low MKI differentiating tumour or 1.5 years with a low or intermediate MKI and a differentiating or partially differentiating tumour.

Unfavourable Histological Features: The unfavourable histological category encompasses all other combinations.

The course of treatment depends on the child's age, disease stage, risk level, and tumour location. The following are the risk categories:

- Low Risk Neuroblastoma: Children need immediate medical attention. If the infant is under the age of six months, the tumour does not require treatment and disappears on its own.
- Children with neuroblastoma of intermediate risk must have surgery to remove the malignant cells or tumour.
- Treatment for high-risk neuroblastoma consists of a mix of chemotherapy, surgery, radiation, high-dose chemotherapy with stem cell rescue, and immunotherapy.^[2]

Importance of Shimada Categorization: The histopathologic classification of neuroblastoma patients created by the Shimada classification is a significant contribution. Children's Cancer Group treats around 295 cases of neuroblastoma each year; this classification

system was analysed and correlated with patient survival (CCG). Important characteristics of this grouping are as follows:

- The patient's chronological age.
- The measure of neuroblast differentiation.
- Schwannian stromal maturation.
- The MKI (Mitosis-karyorrhexis index).
- The Nodular Patterns.^[3]

The following is a list of Favourable histologic groups:

- Any age group with stroma-rich tumours devoid of nodularity.
- Patients younger than 18 months with neuroblastic (differentiated or undifferentiated) neoplasms with a mitotic index (MKI) of 200/5000 (200 karyorrhectic cells/5000 scanned cells).
- Patients with tumours that are stroma-poor, have an MKI of 100/5000, and have well-differentiated tumour cells.

The following is a list of Unfavourable histologic groups:

- Patients with stroma-rich tumours with a nodular appearance, regardless of age
- Patients of any age who have tumours that are low in stroma and have either undifferentiated or differentiated neuroblasts and an MKI of over 200/5000.
- Patients older than 18 months who have tumours that are deficient in stroma, include undifferentiated neuroblasts, and have MKIs above 100/5000.
- Patients older than 60 months with a low MKI value (100) and differentiated neuroblasts without stroma.^[3]

Methodology

Professional prognosis for neuroblastoma includes a thorough neurological and physical assessment. The child's nerve function, coordination, and reflexes are evaluated during the neurological exam. Specialists recommend multiple examinations to ascertain the correct diagnosis, assess the extent of any cancerous spread, and determine the best course of therapy based on the patient's risk profile.^[4]

Classification of images by computer-assisted systems: Patients' chances of survival and treatment options can improve if cancer is detected early. Medical images such as mammograms, ultrasounds, magnetic resonance imaging, and microscopic images are routinely employed in cancer diagnosis. To increase diagnosis accuracy, computer-aided diagnosis (CAD) technologies have lately been utilised to assist clinicians in cancer diagnosis. CAD can help reduce missed cancer lesions due to physician fatigue, reduce workload and data overloading, and reduce image reader variability. This study provided a framework of CAD systems for cancer diagnosis based on medical images. The proposed study aids doctors in detecting suspicious regions using various medical imaging modalities and classifying such regions as normal or abnormal.

Data collection: Data sets were obtained from the Image Bank and the American Society of Hematology. The image dataset used includes 36 NBL patients representing all neuroblastic grading subgroups. All of the photographs have a 40X resolution and have been stained with the H&E Staining technique. The developed classification method and graphical user interface are created using MATLAB (The MathWorks, Inc., Natick, MA). With an i3 Intel Processor, the operating system is Windows 10 Home Premium.^[5]

Organization of paper: Below is a breakdown of how this paper is structured: The second section examines the methods used by earlier researchers for data segmentation and classification. In Section III, we address an overarching perspective of the proposed system and the method of data collecting. In section VI, we detail the specifics of our implementation of a two-stage binary classification process for FL pictures stained with H&E.^{5]} In Chapter 5, we discuss the procedures that were followed. Section VI contains the multistage experiments' final results. Section VII contains the discussion of the summary and final comments.

Segmentation & Analysis of Neuroblastoma: A risk-classification algorithm for patients with a fresh diagnosis of neuroblastoma has been the subject of extensive research and development. Most collaborative groups use a method that takes into account both the evaluation of specific biologic characteristics and the examination of easily measurable clinical variables such patient age and tumour stage. Because tumours with biologic properties

linked with a benign clinical outcome are more common in younger individuals, age at diagnosis is used as a proxy for these underlying biologic qualities. Although age is a continuous variable in prognosis, for clinical purposes, a cutoff threshold of 12 or 18 months of age has been adopted. Infants with locally advanced tumours are almost always treated, and this is frequently accomplished without the use of cytotoxic medication. However, due to the condition's relative rarity and the developing nature of genetic diagnostics, it has been difficult to establish a decision for people who fall somewhere in the middle.^[6]

Proposed Strategies: In this investigation, H&E-stained NB cross-section histological pictures are analysed quantitatively using an automated grading system. Every step of the image analysis pipeline is based on a multi-resolution paradigm, emulating the way pathologists analyse tissue samples under the microscope. The discovered technique can be used on low-resolution images while still keeping sufficient image details for grading. To make reliable judgements, it is necessary to segment images to extract the most informative regions at each level of the image hierarchy.

Grading accuracy and system efficiency are both enhanced by the methodical selection of the optimal subset of characteristics. A prognostic panel with numerous pathologists is simulated by using several classifiers to investigate various regions of the feature space. The proposed system has the potential for NB grading evaluations based on its competitive classification accuracy and high throughput performance.^[7]

It cannot be stressed enough that a pathologist should always be utilised with a computer-assisted grading method. On the contrary, it should be used just as a tool to help make choices. When there is a discrepancy between the computer system and the physicians' assessments, the humans always have the last say (pathologists).

One of the primary paths toward understanding form and function has been the endeavour to identify and locate the molecules that make up the components of live cells and tissues. The method's goal was to establish a causal connection between structure and substance. The labeled-antibody approach is one of the most sensitive means of doing this.

In its simplest form, an antibody is a stain that is produced from a purified component of a cell, tagged with

a marker, and then applied to a tissue section. However, the labeled-antibody method requires not only the production and use of an antibody, but also the meticulous preparation of tissue to be stained with the antibody, all of which must be performed in accordance with a specific protocol.

The algorithm is described as follows,

Step 1: The image dataset is undergoes the following process

Step 2: The image from the dataset gets binarized .Image Binarization is the conversion of the document image into the bi-level document image.

Step 3: After the process of Binarization of the image it undergoes Color Analysis. It is the process of analyzing the amount of the color used in the Image.

Step 4: Color Segmentation is done after the procedure of color analysis is done. Color Segmentation, a process where the cells are identified on the basis of color and gets distinguished

Step 5: Via MATLAB used STREL() function to distinguish the Circles present in the Image

Step 6: After the Step5 we'll get the raw image of the irregular cells

Step 7: Calculate the Major and the Minor Axis of the cell that has been extracted

Step 8: This is the last Step i.e If the ratio of the major and the minor axis of the cell is greater than 1, then it is the cancer cell . Else, a non-Cancerous Cell.

Image Assisted Classification of Neuroblastoma:

• IMAGE SET

All tumour slides utilised in the image dataset technique are selected such that they are excellent representations of distinct grade subtypes and contain a sufficient number of cytological components of relevance in the tissue areas. The created classification method and graphical user interface are both made in MATLAB (The MathWorks, Inc., Natick, MA). There are a total of 36 NB instances in the picture collection utilised, one for each of the neuroblastic grading categories.^[9]

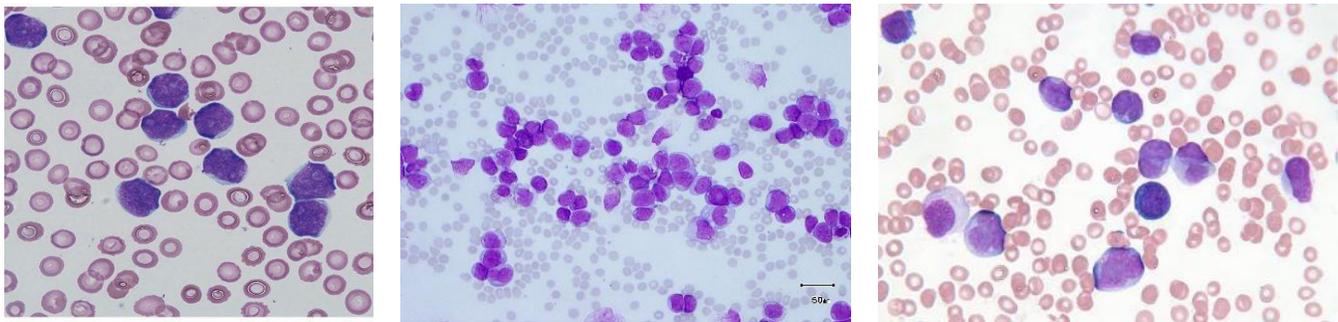


Figure 3. Datasets collected (H&E stained images)

- **Image Acquisition:** During the preparation phase of the image capture procedure, tissue slides are cut to a thickness of approximately 5 micrometres and then immersed in paraffin. The dual staining approach is used to tint each neuroblastoma slide stained with Hematoxylin and eosin (H&E) to heighten the visual contrasts of distinct cytological components. After the picture is stained using the dual staining technique, each prepared tissue slide is put on a scanning platform and scanned using the Scan Scope T2 digitizer, allowing for the clear visibility of tumour structures^[9]
- **Colour segmentation:** Figure 4. Segmented image wherein the red outlined cells depict the regular and blue outlined cells depict the irregular cells

Steps of Process

1. **Read original image:** The original image is read as an input by the “imread” function, and numerous colour variations, such as converting the rgb image to grayscale, have been applied.

The RGB2GRAY function is used to convert the picture to grayscale for improved cell identification.

To facilitate a deeper comprehension of the concept, the cells may be clearly distinguished.

2. **Convert to grayscale:** Using RGB to grey, the original picture is transformed to grayscale.
3. **Red-blue cell separate:** These images have been taken for further detection of the boundaries of blue channel or red channel separately.

```
red=img(:,:,1)
```

```
subplot(4,2,3)
```

```
blue=img(:,:,3)
```

```
subplot(4,2,4)
```

4. **Extract irregular cell:** Irregular cells are identified because they are not totally rounded. They are discovered using the strel function, which is detailed in detail in the matlab function.
5. **Extract regular cell:** Regular cells are completely round cells that are found in cells and are easier to extract. They are also retrieved from the strel function by utilising disc and assigning the radius as parameters for further boundary detection.

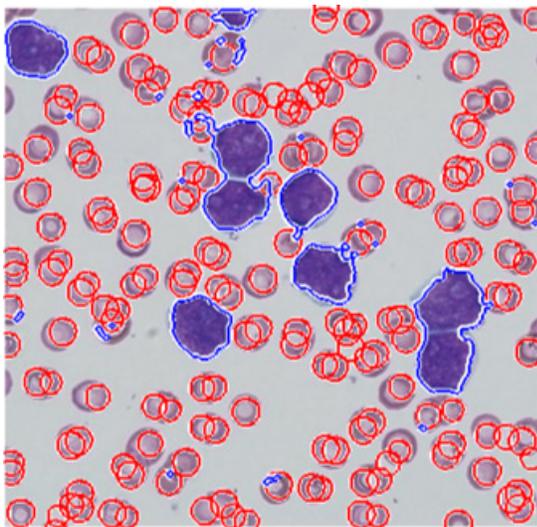


Figure 4. Segmented image wherein the red outlined cells depict the regular and blue outlined cells depict the irregular cells.

6. **Add both images & invert the output:** In order to distinguish between regular and irregular cells, the photos we are now working on are binarized and the black and white are further transformed on the white and black that are exactly opposite sides. We were

able to separate the regular cells from the irregular cells using this method and the “imbinarize” function exclusively.

7. **Count the circle:** For additional detection and computation reasons, the circles that were as shown in Figure 4 discovered, whether regular or irregular, now need to be tallied. Because irregular cells are essentially cancer cells and regular cells, the number of red cells, or normal cells, will always be higher than the number of irregular cells. The project’s primary goal is to find cancer cells and determine whether or not a person is infected. Therefore, this may practically happen based on the tissue cell’s picture alone.^[10]
 - **Boundarization of irregular & regular cells:** Boundarization is the process of dividing cells into smaller units to determine their regularity or irregularity, which is crucial for the early diagnosis of cancerous tissues.

Figure 5. The images acquired after the boundarization

The cells in this instance were coloured red and blue in the H&E stained photos that were used as an input. Therefore, methods were used to identify the red cells as irregular cells, which are therefore cancer cells, and the blue colour cells, which are rounder cells. Figure 5 illustrates how we converted the RGB portion of the image into black and white for clarity’s sake.^[11]

Steps taken for Boundarization are,

- The image is taken as the input
- The image is converted from RGB to GRAY
- The structuring element function “STREL” function is taken where we define parameters as:
 1. Disc
 2. Diamond
 3. Octagon
 4. Line
 5. Triangle
- ‘Imdilate’ function dilates the image it dilates the grayscale, binary, or packed binary image I using the structuring element SE
- And for displaying the original image ‘imtool’ function is used at the end

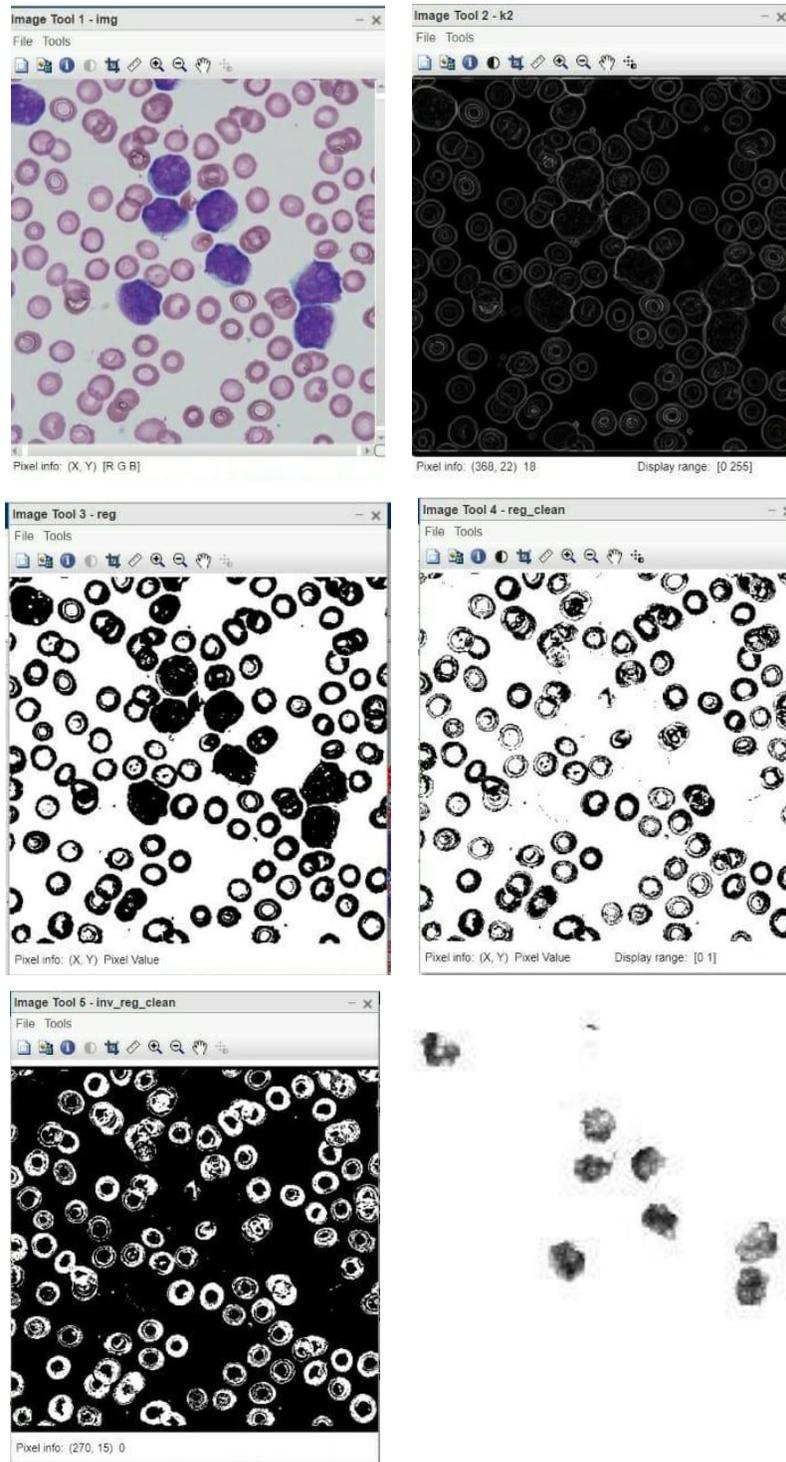


Figure 5. The images acquired after the boundarization

- Major minor axis:** The line segment that joins the two furthest points of an ellipse is known as the main axis and may be seen in Figure 6. The axis that goes through the nearest point is the minor axis, as may be seen in Figure 6. The output image of the boundarization

of irregular cells served as our first input. After preprocessing the image, the noise reduction filtering is finished. Many cells are elongated, as indicated by the dotted line's aspect ratio of 1.^[11]

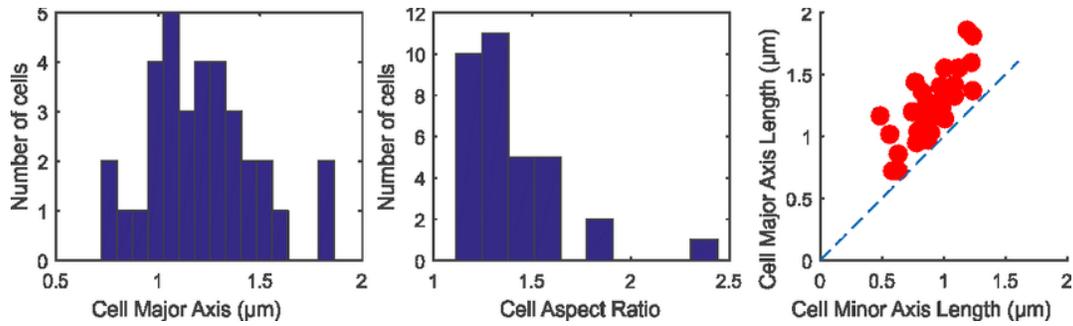


Figure 6. graph depicting the calculation of the major minor axis

- **Cancer Detection:** One of the biggest obstacles to curing cancer is finding it at an early stage. When detected, cancer usually has already invaded many organs and has impacted bodily functions before it is diagnosed. A major focus of current research is on developing better tools for detecting cancer at an early stage.

Result

Before the proposed system can achieve a cost-effective level of grading accuracy, it must undergo extensive training. The diagram depicts a high-level overview of the training–testing process, with solid and dashed arrows representing the online and offline processes, respectively. As the ADP system is educated with increasingly regular patterns, its outputs begin to resemble those of a pathologist. Following the conclusion of the training procedure, testing data is provided to the “educated” system for performance evaluation. The emerging method might provide pathologists and clinicians with a helpful tool for determining the grade of NB.[14] Although the decision-making accuracy of the computerised system appeared promising in our experiments, it should be underlined that its function must always be confined to that of a second reader or pre-screener. In other words, the automated technique is not intended to replace the pathologist, but rather augment the quality prognostic procedure. Due to the importance of neuroblastic differentiation for precise protocol assignment, we will continue to enhance the established system in our future endeavours. Because higher-order choice information can contribute to either a more efficient or more precise global labelling configuration, it is better to develop a labelling strategy that includes decision information from nearby picture tiles. As our present approach only utilises colour and texture information, we will also study the possibility of including a larger range of data in the future. We will also investigate a method for grouping the simplest

training datasets, as data generalisation is a potentially crucial issue that might have a significant effect on overall performance. With the improvement of each of these factors, it is realistic to predict classification accuracy that meets clinical standards.^[14]

Conclusion

The entire image analysis pipeline is intended to function in a setting with several resolutions. The classification accuracy of the system is 87.88 percent. The created approach favours working with low-resolution images that retain sufficient picture details for grading analysis. A sequence of classifiers, imitating the presence of several pathologists within a prognostic panel, is used to examine distinct regions of the feature space. Neuroblastic tumours (NTs) are a group of tumours that includes neuroblastoma, ganglioneuroblastoma, and ganglioneuroma. Currently, researchers from all over the world are working together to evaluate the clinical and biologic characteristics of NTs in order to create treatment plans based on a comprehensive set of International Neuroblastoma Risk Groups. Both an international Neuroblastoma Staging System and a set of International Neuroblastoma Response Criteria have been established. To far, international cooperation has resulted in the creation of both the International Neuroblastoma Response Criteria and the Global Neuroblastoma Staging System. A worldwide pathology classification has been proposed by the International Neuroblastoma Pathology Committee (INPC), which has been actively involved in this effort since its inception in 1994.

Clinical features of NTs that are “unexpected” include involution/spontaneous regression, maturation, and aggressive progression, leading many oncologists and researchers to label NTs as “enigmatic.” The data gathered from both clinical and fundamental studies has allowed for a new level of understanding of NTs

(i.e., NTs are “heterogeneous,” with their individual biologic features intimately tied to their unique clinical behaviour). The extent to which neuroblasts mature into ganglion cells has long been recognised as the single most important morphologic trait for NT prognosis. Several histopathologic grading systems for NTs have been developed throughout the years, but none of them has been widely used. As a first step, Shimada distinguished NTs by age, classifying them as either Schwannian stroma-rich or stroma-poor tumours.

They coined the term “mitosis-karyorrhexis index” to describe one of the prognostic indicators (MKI). Joshi et al. revised the current classification by asserting that tumor-associated calcification is prognostic whereas a high mitotic rate is detrimental to the patient’s outlook. Key biological features of neuroblastic tumours have affected our knowledge during the past decade. Neoplasms are the medical term for tumours. The difficulty of creating a disease categorization system that can be replicated and has biological relevance is a problem that has plagued every system that has attempted to do so.

The main international collaboration on NTs provided support for the INPC’s four-year activities, which are summarised in this paper:

- Using the consensus diagnoses to evaluate the prognostic significance of the morphologic features and their combinations;
- Developing consensus diagnoses to support consistent morphologic feature criteria.

The goal of the INPC is to offer a prognostically beneficial, physiologically significant, highly repeatable, and user-friendly Neuroblastoma Pathology Classification. The precise standards for the morphologic characteristics of the NTs employed in this investigation were previously published. We also offer a suggestion or advice for surgical pathologists to use when characterising and predicting NTs as part of the current investigation.

Ethical Clearance: Taken

Conflict of Interest: Nil

Source of Funding: Self

References

1. Georgia Papaioannou and Kieran McHugh, “Neuroblastoma in childhood: review and radiological findings”, 2005 Sep 30.
2. J. Kong, a,d,* O. Sertel, a,d H. Shimada, b K.L. Boyer, c J.H. Saltz, d and M.N. Gurcand,” Computer-aided evaluation of neuroblastoma on whole-slide histology images: Classifying grade of neuroblastic differentiation” 2009 Jun.
3. Kanika A Bowen, Dai H Chung. “Recent advances in neuroblastoma”, 2009 Jun;
4. Metin N Gurcan 1, Laura E Boucheron, Ali Can, Anant Madabhushi, Nasir M Rajpoot, B Yener,” Histopathology Image Analysis:Review ” 2009 Oct 30.
5. S Ley, J Ley-Zaporozhan, P Günther, H E Deubzer, O Witt, J-P Schenk.” Neuroblastoma Imaging” 2010 Dec 17.
6. Kushner BH. Neuroblastoma: a disease requiring a multitude of imaging studies. *J Nucl Med.* 2004;45:1172–88. - PubMed
7. Park JR, Hogarty MD, Bagatell R, et al. Chapter 23: Neuroblastoma. In: Blaney SM, Adamson PC, Helman LJ, eds. *Pizzo and Poplack’s Principles and Practice of Pediatric Oncology.* 8th ed. Philadelphia Pa: Lippincott Williams & Wilkins; 2021,” Key Statistics About Neuroblastoma” April 28, 2021.
8. Norman J Lacayo, ”What is the Shimada histopathological classification system of pediatric neuroblastoma” May 14, 2021.
9. Quoc Dang Vu, Simon Graham, Tahsin Kure*, Minh Nguyen Nhat To, Muhammad Shaban, Talha Qaiser, Navid Alemi Koohbanani, Syed Ali Khurram, Jayashree Kalpathy-Cramer, Tianhao Zhao³, Rajarsi Gupta, Jin Tae Kwak¹, Nasir Rajpoot, Joel Saltz and Keyvan Farahani, “Methods for Segmentation and Classification of Digital Microscopy Tissue Images”, 02 April 2019.
10. <https://in.mathworks.com/help/images/color-based-segmentation-using-the-l-a-b-color-space.html>
11. Akira Nakagawara, Yuanyuan Li, Hideki Izumi, Katsumi Muramori, Hiroko Inada, Masanori Nishi,”Neuroblastoma”,2018 Mar.
12. <https://in.mathworks.com/help/images/ref/im2bw.html>
13. <https://imagebank.hematology.org/>
14. HuZilonga, Tang, Jinshana, Wang, Ziming, Zhang, Kaiac, Zhang, Linga, Sun, Qingling, “Deep learning for image-based cancer detection and diagnosis– A survey”, Nov 2018.